Do pervasive economic factors explain momentum?

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Abstract

This thesis investigates the relationship between the profitability of momentum strategies and macroeconomic variables associated with the business cycles. We hypothesize that momentum is a risk factor that correlates with economic dynamics, which drive stock prices. We apply the two-state Markov regime switching model of Hamilton (1989) to capture the dynamic behavior of the time series of momentum return across different regimes. We include both univariate and multivariate regressions to examine the explanatory power of independent variables during different states. Moreover, we explore whether economic dynamics and investor sentiment are the only sources of the pricing effect of momentum. We adjust the momentum returns for selected macroeconomic variables, risk factors and proxy for investor sentiment. We define the residuals from the model as "pure momentum" and test the pricing capability of pure momentum in a standard asset pricing model. Using a sample of monthly data of US market covering the period between August 1962 and December 2014, we document that macroeconomic factors, risk factors and investor sentiment are unable to fully explain the momentum profits. Using a sample of monthly return on portfolios constructed by double-sorting stocks on size and book-to-market equity ratio, which include NYSE, AMEX, and NASDAQ stocks, we show that the pricing capability of momentum cannot be entirely explained by macroeconomic variables, risk factors and investor sentiment.

Key words: *momentum profits, macroeconomic variables, Markov regimes, excess stock returns*

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1. Introduction

Sharpe (1964) and Lintner (1965) established the classical Capital Asset Pricing Model (CAPM) to describe the relationship between the expected return of assets and their risk. The model indicates that the expected return on an asset is only related to its market beta, which measures the systematic risk of the asset. Fama and French (1993) derived a three-factor model by adding the size and value risk factors to the traditional CAPM. The Fama-French three-factor model appears to help explain the cross-section of average stock returns and has been widely used in the research of asset pricing.

Jegadeesh and Titman (1993) investigate trading strategies that involve buying stocks that have performed well in the past and selling stocks that have performed poorly in the past. Jegadeesh and Titman find that these strategies generate significant positive returns. Their study indicates that the stock market appears to exhibit the continuation of short-term returns, which is known as the short-term momentum.

Afterward, Fama and French (1996) test the Fama-French three-factor model by running regressions of monthly returns on double-sorted portfolios on the three risk factors. Their results show that the three-factor model can explain certain anomalies documented by previous literature. However, they conclude that the three-factor model fails to explain the continuation of short-term momentum anomalies raised by Jegadeesh and Titman (1993). Consequently, Carhart (1997) extends the Fama-French three-factor model to a four-factor model by including a momentum factor.

Many researchers have investigated the profitability of momentum strategies and have given interpretations regarding momentum profits. There are mainly two explanations for the momentum anomaly among academics. The first is behavioral, in which momentum is attributed to investors' sentiment to news and events. Jegadeesh and Titman (1993) document that momentum profits are related to market underreaction to the firm-specific information. Furthermore, Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein

(1999) provide behavioral models that capture the momentum anomaly subject to investors' overreaction or underreaction. In addition, Veronesi (1999) develops a rational expectations equilibrium model of asset prices to show the overreaction and underreaction of stock prices conditional on business states. Furthermore, Baker and Wurgler (2006) show that investor sentiment has significant effects on the cross-section of stock prices. The other explanation for the momentum anomaly is based on alternative measures.

Under the risk explanation, a number of studies investigate the relationship between momentum and economic dynamics. Liew and Vassalou (2000) test the relationship between the profitability of the size factor (small minus big, SMB), value factor (high minus low, HML), and momentum factor (winner minus loser, WML) and future Gross Domestic Product (GDP) growth using data from ten developed markets over the period 1978 to 1996. They show that SMB and HML, but not WML, are significantly positively related to future GDP growth. Later on, Chordia and Shivakumar (2002) explain part of momentum profits using common macroeconomic variables associated with business cycles, such as lagged macroeconomic variables, dividend yield, default spread, yield on three-month T-bills, and term structure spread. Consequently, Cooper, Gutierrez, and Hammed (2004) examine the macroeconomic factor model by Chordia and Shivakumar (2002). They show that the macroeconomic model has no explanatory power for momentum profits. In addition, Griffin, Ji, and Martin (2003) examine the robustness of the unconditional model of Chen, Roll, and Ross (1986) and the conditional macroeconomic model of Chordia and Shivakumar (2002) based on international data from 39 countries during various time periods. They conclude that momentum profits cannot be explained by either macroeconomic model.

The object of our study is to explore the relationship between the profitability of momentum strategies and macroeconomic variables associated with the business cycles. We expect that momentum is a risk factor that correlates with economic dynamics, which drive stock prices. We apply a Markov regime switching model to capture the dynamic behavior of the time series of momentum return across different regimes. Moreover, we explore whether economic dynamics and investor sentiment are the only sources of the pricing effect of momentum returns. We adjust the momentum returns for selected macroeconomic variables and proxy for investor sentiment. We define the residuals from the model as "pure momentum" and test the pricing capability of pure momentum in a standard asset pricing model.

Recently, researchers have used various methods to determine whether the economy is in a good state (expansion) or in a bad state (contraction) to explain the relationship between momentum and macroeconomic variables across different economic phases. Liew and Vassalou (2000) define expansion as those states that perform in the highest 25% of future GDP growth and contraction as those states with the lowest 25% of future GDP growth. Chordia and Shivakumar (2002) divide sample into expansionary and recessionary periods based on the NBER definition. Cooper, Gutierrez, and Hammed (2004) define expansion as states when the three-year lagged market return is non-negative and contraction as those when the three-year lagged market return is negative.

To our knowledge, there are very few studies that investigate momentum returns under a Markov regime switching framework. In this study, we propose both univariate and multivariate Markov regime switching models to examine the explanatory power of independent variables during different states. Our assumption is that the dynamic process of momentum return conditional on economic regimes is determined by the value of an unobserved random variable. The state-dependent parameter estimates in our model are driven by this latent state variable. We apply a two-state regime switching model in our study.

The rest of this thesis is organized as follows. Chapter two reviews the relevant literature on asset pricing anomalies and discussion on momentum profits. In chapter three our methodology is presented. We describe our data collection in chapter four.

Chapter five reports the empirical findings. Finally, Chapter six presents our conclusions.

2. Literature Review

2.1 Asset Pricing Anomalies

In the classical Capital Asset Pricing Model (CAPM) of William Sharpe (1964) and John Lintner (1965), the expected return on an asset is only related to its market beta, which measures the systematic risk of the asset.

A number of studies have shown that certain asset pricing anomalies cannot be explained by the standard single-factor CAPM. Basu (1977) documents that future returns on stocks are negatively related to their price/earnings ratios. He finds that from April 1957 to March 1971, stocks with low price/earnings ratios earn higher risk-adjusted returns than stocks with high price/earnings ratios. Banz (1981) reports that small market capitalization stocks tend to have higher average returns than large market capitalization stocks. His study examines the relationship between the total market value of the common stock and its return for the period 1936 to 1975. He finds that the market value of a stock adds to the explanation of the average returns provided by the market beta, which is known as the size effect.

Empirical evidence shows that there are other variables which contribute to explain the cross-section of average returns. Stattman (1980) and Rosenberg, Reid, and Lanstein (1985) document that average stock returns in the U.S. market are positively related to the book-to-market equity ratio. Furthermore, Chan, Hamao, and Lakonishok (1991) provide evidence showing a positive and significant relationship between the book-to-market ratio and the expected returns. They investigate the monthly data in the Japanese stock market from January 1971 to December 1988. In addition, they find that cash flow/price ratio is positively and significantly related to the expected returns. Bhandari (1988) finds that there is a positive and significant relationship between the expected common stock returns and the debt-equity ratios. He finds that leverage helps explain the cross-section of average stock returns when controlling for beta and firm size, both including and excluding a January dummy. Lakonishok, Shleifer, and Vishny (1994) use US stock returns and company characteristics for the sample period April 1963 to April 1990 to investigate the relationship between firms' past performance and stock returns. They find that variables including book-to-market ratio, earnings/price ratio, cash flow/price ratio, and sales growth have explanatory power for average stock returns.

Fama and French (1992) demonstrate that the combination of size and book-to-market equity helps explain average returns. Following Fama and MacBeth (1973), they apply the cross-sectional regression approach for the period 1963 to 1990. Their results indicate that size and book-to-market combine to capture the cross-sectional variation in average stock returns and absorb the roles of leverage and earnings/price ratios. Fama and French (1993) derive a three-factor model by adding size and value risk factors to the traditional CAPM. They define the size factor (SMB, small minus big) as the difference between the return on a portfolio of small market capitalization stocks and the return on a portfolio of large market capitalization stocks. Similarly, they define the value factor (HML, high minus low) as the difference between the return on a portfolio of high book-to-market stocks and the return on a portfolio of low book-to-market stocks. Their three-factor model appears to help better explain the cross-section of average stock returns.

DeBondt and Thaler (1985) define portfolios with lower previous returns as loser portfolios and those with higher previous returns as winner portfolios. They report that when formed on the returns of the past three to five years, loser portfolios outperform the market whereas winner portfolios underperform the market in the subsequent period. They use a data set of monthly return for NYSE common stocks from January 1926 to December 1982. Their results are consistent with investors' overreaction, and reveal the long-term reversal anomaly in U.S. stock market. In contrast, Jegadeesh and Titman (1993) investigate trading strategies which buy stocks that have performed well in the past and sell stocks that have performed poorly in the past. They show that these strategies realize significant positive returns over 3-month to 12-month holding periods, using cross-sectional daily returns from the CRSP over the 1965 to 1989 period. Their study indicates that the stock market appears to exhibit the continuation of short-term returns, termed short-term momentum. Furthermore, Jegadeesh and Titman (2001) reexamine the profitability of momentum strategies in cross-sectional stock returns. They document that the momentum profits which have continued over 1990 to 1998 are similar to the profits found in the earlier time period.

Fama and French (1996) test the Fama-French three-factor model by running regressions of monthly returns on double-sorted portfolios on the three risk factors. Their results show that certain anomalies documented by previous literature can be explained by the three-factor model during the period July 1963 to December 1993. They report that the three-factor model capture the returns to portfolios formed on earnings/price ratio, cash flow/price ratio, sales growth and the reversal of long-term past returns.

However, Fama and French (1996) conclude that the three-factor model fails to explain short-term momentum anomalies. In the three-factor regressions for monthly returns on portfolios formed on past returns, the intercepts are strongly negative for short-term losers and strongly positive for short-term winners. Compared with many other asset pricing anomalies, the short-term momentum anomalies are robust. Consequently, Carhart (1997) extends the Fama-French three-factor model to a four-factor model by including a momentum factor. Similar to the Fama French three factors, momentum (MOM) is defined as the average return on the high prior return portfolios minus the average return on the low prior return portfolios. Carhart documents that the four-factor model substantially reduces the pricing errors presented in the three-factor model and well explains the cross-sectional average stock returns.

2.2 Momentum Anomaly and Explanations

As the only remaining CAPM-related anomaly unexplained by the Fama-French three-factor model, the profitability of momentum strategies has intrigued many researchers.

Since the publication of the study by Jegadeesh and Titman (1993), a number of empirical studies have examined the momentum anomaly. Rouwenhorst (1998) studies the international return momentum using data of 2,190 stocks from 12 European countries for the period 1978 to 1995. He reports that momentum is pervasive in all 12 markets in the sample. Subsequent researchers such as Rouwenhorst (1999), Liu, Strong, and Xu (1999), Chan, Hameed, and Tong (2000), Griffin, Ji, and Martin (2003), Chui, Titman, and Wei (2010) have also shown that momentum anomaly is prevalent in other international equity markets. Moskowitz et al. (2012) finds the momentum effect significantly exists in time series using data of futures prices for the period January 1965 to December 2009. Moskowitz and Grinblatt (1999) find that momentum exists across industries. They construct 20 value-weighted industry portfolios formed monthly for the period July 1963 to July 1995 and observe that momentum strategies trading on industry portfolios realize significant profits. Asness, Moskowitz, and Pedersen (2013) find the momentum effect across asset classes including individual stocks, country equity index futures, government bonds, currencies and commodity futures.

There are mainly two categories of explanations for the momentum anomaly among academics. The first is behavioral, in which momentum is attributed to investors' sentiment to news and events. Trading strategies that select stocks according to their previous performance are profitable if stock prices either overreact or underreact to good or bad information. A common explanation for profits to momentum strategies is that investors tend to underreact to news such as earning announcements. Jegadeesh and Titman (1993) investigate the source of the observed momentum profits and document that momentum profits are related to market underreaction to firm-specific information. They present a potential interpretation that investors who buy past winners and sell past losers tend to push the stock prices away from their rational market value temporarily so that stock prices display underreaction to news. Barberis, Shleifer, and Vishny (1998) propose a behavioral model based on psychological evidence. They show that their model generates the empirical predictions observed in the data. In their study, they make assumptions that the earnings follow a random walk, the investor is risk-neutral, and the model is specified as Markov process. They demonstrate that their model captures the stock prices' underreaction to earnings announcement as well as describing investor sentiment. Similarly, Daniel, Hirshleifer, and Subrahmanyam (1998) present a behavioral model is based on psychological concepts of investor overconfidence and self-attribution. In addition, Hong and Stein (1999) generate a behavioral theory in which they include two groups of agents, newswatchers and momentum traders, to explain the market underreaction and overreaction. Furthermore, Veronesi (1999) develops a dynamic, rational expectations equilibrium model of asset prices. He assumes that stock dividends are generated by a Gaussian diffusion process and the drift rate is not observed by investors. His results show that stock prices overreact to bad news in good times and underreact to good news in bad times. In addition, Baker and Wurgler (2006) document that investor sentiment has significant effects on the cross-section of stock prices. They generate a proxy for investor sentiment as the measure of investors' beliefs about future asset prices and investment risks. They report that returns are relatively high for small, new, high volatility, and extreme growth stocks when the beginning period proxy for investor sentiment is low. Similarly, many other researchers demonstrate that investor sentiment affects stock excess returns and causes nonlinearity and asymmetry (Brown and Cliff (2004), Schmeling (2009), Chen (2013), Ni, Wang, and Xue (2015), Chang, Hsieh, and Wang (2015), Yang and Zhou (2015)).

The other explanation for the momentum is based on concepts of risk. Johnson (2002) suggests that the phenomenon of momentum is associated with a risky growth rate. He assumes that the economy and the asset cash flow are geometric Brownian motion processes. His model shows that the volatility of the cash flow growth rate (i.e. the growth rate risk), accounts for the momentum anomaly. Furthermore, Sagi and Seasholes (2007) report that firm-specific attributes such as revenues, costs, and growth options affect the profitability of momentum strategies. Using data from CRSP and Compustat over the period 1963 to 2004, they show that return autocorrelation is positively related to revenue volatility and the market-to-book ratio is negatively related to costs. They also construct momentum portfolios after sorting stocks by revenue volatility, costs, and market-to-book ratio. Their results show that momentum strategies applied to high revenue volatility firms, low cost firms, and high market-to-book firms all outperform the traditional strategy. They also consider the impact of market states. They find that momentum strategies produce higher profits in up market states than in down market states.

2.3 Momentum Profits and Business Cycle Risk

Recent studies investigate the relationship between momentum and economic dynamics. Liew and Vassalou (2000) test the relationship between the profitability of SMB (small minus big), HML (high minus low), and WML (winners minus losers) and future Gross Domestic Product (GDP) growth using data from ten developed markets over the period 1978 to 1996. They run regressions of GDP growth on factors and variables including market returns, SMB, HML, WML, T-bills rate, dividend yield, term spread, and growth rate of industrial production. They provide evidence that SMB and HML are significantly positively related to the future GDP growth. However, they find little evidence that the returns of WML are related to future growth in the real economy.

Chordia and Shivakumar (2002) investigate the relationship between profits to momentum strategies and common macroeconomic variables associated with the business cycles. The authors rank all NYSE-AMEX stocks on the monthly CRSP files into deciles based on their prior returns and form 10 equal-weighted portfolios for the period 1926 to 1994. They divide the sample into expansionary and contractionary periods based on the NBER definition and find that returns on momentum portfolios are positive (negative) during expansion (recession) periods. Using a set of lagged macroeconomic variables related to the business cycle to predict next-month returns, the authors show that the predicted portion of returns is the source of the momentum profit. They adjust the momentum returns by selected variables and define the unexplained portion of returns as the intercept plus the residual. Then they test whether the unexplained portion of returns is significantly different from zero. Their results show that lagged macroeconomic variables including dividend yield, default spread, yield on three-month T-bills, and term structure spread help explain momentum strategy profits.

However, Cooper, Gutierrez, and Hammed (2004) examine the macroeconomic factor model by Chordia and Shivakumar (2002) for both up and down market states. They show that the macroeconomic model has no explanatory power for the asymmetry of momentum profits between states. They create 25 double-sorted portfolios by predicted returns from the macroeconomic factor model and lagged six-month returns of the stocks. The authors also document that from 1929 to 1995, the mean monthly momentum profits is 0.93% when three-year lagged market returns is positive (up market states) and -0.37% when three-year lagged market returns is negative (down market states).

Other researchers have investigated the relationship between momentum profits and macroeconomic risk on a global basis. Griffin, Ji, and Martin (2003) examine the robustness of the unconditional model of Chen, Roll, and Ross (1986) and the conditional macroeconomic model of Chordia and Shivakumar (2002) based on data from 39 countries for various periods. They conclude that momentum profits cannot be explained by either the Chen et al. (1986) factors or the Chordia and Shivakumar (2002) macroeconomic model. They also document that international momentum profits are generally positive in both good and bad macroeconomic states. Similarly, Antoniou, Lam, and Paudyal (2007) find that the predictive model of Chordia and Shivakumar (2002) cannot explain the profitability of momentum strategies in these markets. They study the data from France, Germany and UK markets for the period 1977 to 2002 and run regressions controlled for business cycles variables, Fama-French three factors, firm characteristics and behavioral biases. Following Avramov and Chordia (2006), the authors apply a conditional model which allows factor loadings to vary with firm-specific variables. They find that Business-cycle variables and behavioral biases can explain the profitability of momentum trading. They find that most of the European momentum payoffs are driven by systematically asset mispricing changes with international business cycles.

2.4 Application of Markov Regime Switching Models and Residual Analysis

Time series of many economic and financial variables exhibit structural breaks associated with significant changes in level of economic activity, financial crises and bubbles, dramatic changes in government policies, or wars. The Markov regime switching model of Hamilton (1989) is a nonlinear economic model which captures the dynamic behavior of the economic time series through different regimes. He describe the consequence of the structural changes with an autoregressive process driven by an unobserved state variable which determines the regime shifts and follows a first-order K-state Markov chain. Krolzig (1997) develops a multivariate version of the Markov regime switching autoregressive (MS-AR) model using a Markov regime switching vector autoregressive (MS-VAR) model to replace the univariate regime switching model.

Researchers have also applied the Markov regime switching approach to capture the cyclical process of US real GNP growth rates (Durland and McCurdy (1994)), industrial production (Filardo (1994)), real GDP (Raymond and Rich (1997)), interest rates (Ang and Bekaert (2002), Bansal, Tauchen, and Zhou (2004)), foreign exchange rates (Lee and Chen (2006)), oil futures prices (Fong and See (2002)), the relationship between US crude oil and stock market prices (Balcilar, Gupta, and Miller (2015)), and stock returns (Whitelaw (2000), Guidolin and Ono (2006), Bhar and Malliaris (2011)).

It is common to use a two-regime specification to characterize two economic cycles (expansion and contraction) which coincide with the concept of the National Bureau of Economic Research (NBER) business cycles dating procedure (Filardo (1994), Whitelaw (2000), Bansal, Tauchen, and Zhou (2004)). Other studies extend the two-regime model to an N-regime model in order to describe the dynamic process more precisely. Others use a multivariate regime switching model to explain several jointly correlated variables across regimes. Bhar and Malliaris (2011) apply a three-regime model to examine the relationship between US stock returns, fundamental macroeconomic variables and momentum returns (as a behavioral variable). They define economic regimes as low-volatility, medium-volatility, and high-volatility. They use monthly data from June 1965 to December 2008 including dividends, inflation rate, unemployment rate, and momentum returns. Guidolin and Ono (2006) use a four-state multivariate regime switching VAR model to investigate the relationship between US asset returns and macroeconomic variables. Using monthly data from December 1926 to December 2004, they document that the four-regime model performs well.

Although the Markov regime switching model is broadly used in many areas, there are very few studies discussing momentum returns under a Markov regime switching framework. Previous studies use various concepts to determine a good state (expansion) from a bad state (contraction). Liew and Vassalou (2000) define expansion (contraction) as those states with the highest (lowest) 25% of future GDP growth. Chordia and Shivakumar (2002) divide their sample into expansionary and recessionary periods based on the NBER definition. Cooper, Gutierrez, and Hammed (2004) define expansion (contraction) as states when the three-year lagged market return is non-negative (negative).

Very few studies explore the residual of Markov regime switching model. Hardy, Freeland and Till (2006) propose a residual analysis on regime switching process. Since we do not directly observe the regimes, it is uncertain which regime the process is in, and it is difficult to identify the residuals. In order to solve this problem, they define two approaches to determine the residuals. The first approach is to calculate the weighted average of the two residuals from two regimes using the conditional probability for each regime. The second approach is to extract the residual with higher probability, which is identical to a zero-one weighting. They find similar results when testing the normality of residuals generated by these two approaches.

3. Methodology

As a nonlinear economic model which captures the dynamic behaviors of economic and financial time series through different regimes, the Markov regime switching model of Hamilton (1989) is able to specify the mean and the variance as regime-dependent, which provides a more insightful interpretation of the independent variables explanatory power. Although the Markov regime switching model is broadly used in many areas of economy, there are very few studies that investigate the momentum returns under a Markov regime switching framework.

In this study, we fit a Markov regime switching model to test whether the profitability of momentum strategies is related to macroeconomic variables associated with business cycles and investor sentiment. We include both univariate and multivariate regressions to examine the explanatory power of independent variables during different states. In addition, we test whether macroeconomic variables and investor sentiment are the only sources of the pricing effect of momentum returns. In order to capture the unexplained portion of momentum returns, we extract the residuals from the regime switching regressions and test whether they can be priced in a standard asset pricing model.

In this chapter, we first describe a simple linear regression model in section 3.1. In section 3.2, we present the Markov regime switching model in both univariate and multivariate frameworks. In section 3.3, we describe the procedure of extracting the residuals from the regime switching regressions and the asset pricing test.

3.1. Ordinary Linear Regression of Momentum Returns

We begin with a simple ordinary linear regression. The motivation of the OLS model is to obtain a general benchmark for coefficients by regressing momentum returns on lagged values of macroeconomic variables:

$$MOM_t = \alpha + \beta_1 DIV_{t-1} + \beta_2 TB_{t-1} + \beta_3 TERM_{t-1} + \beta_4 CRD_{t-1} + \beta_5 IDPgrowth_{t-1} + \beta_6 INF_{t-1} + \varepsilon_t \qquad (1)$$

where MOM_t is the momentum return in month t; DIV_{t-1} is the dividend yield in month $t-1$; TB_{t-1} is the yield on three-month T-bills in month $t-1$; $TERM_{t-1}$ is the term spread in month $t-1$; CRD_{t-1} is the credit spread in month $t-1$; $IDPgrowth_{t-1}$ is the growth rate of Industrial Production in month $t-1$; INF_{t-1} is the inflation rate in month $t-1$; and ε_t express the residual of regression in month t. We also present the model as:

$$y_t = \alpha + \sum_{i=1}^{I} \beta_i MacroVariables_{t-1} + \varepsilon_t \qquad (2)$$

where y_t denotes momentum return in month t (MOM_t), $MacroVariables_{t-1}$ stands for value of DIV, TB, $TERM$, CRD, $IDPgrowth$ and INF in month $t-1$, α is the intercept, β_i is the coefficient of the ith independent variable, ε_t is the residual of regression in month t, and I is the number of independent variables.

We extend the ordinary linear regression by adding risk factors and a proxy for investor sentiment as independent variables:

$$MOM_t = \alpha + \beta_1 DIV_{t-1} + \beta_2 TB_{t-1} + \beta_3 TERM_{t-1} + \beta_4 CRD_{t-1} + \beta_5 IDPgrowth_{t-1} + \beta_6 INF_{t-1} + \beta_7 MKT_t + \beta_8 SMB_t + \beta_9 HML_t + \beta_{10} Liquidity_t + \beta_{11} CCI_t + \varepsilon_t \qquad (3)$$

where MKT_t, SMB_t and HML_t are the market factor, the size factor and the value factor in the Fama-French three-factor model in month t, respectively; $Liquidity_t$ is the Pastor-Stambaugh (2003) liquidity factor in month t; CCI_t is the change in the Consumer Confidence Index in month t.

3.2. Markov Regime Switching Model

In this study, we fit a Markov regime switching model to test whether the profitability of momentum strategies is related to macroeconomic variables associated with business cycles. The regime switching model assumes an unobserved random variable is the dynamic process determining the regime. We apply a two-state regime switching model in our study. The latent variable S_t, which is a regime or a state, follows a first-order K-state Markov chain. The probability that S_t is equal to a certain value only depends on the most recent past value S_{t-1}.

$$P\{S_t = j | S_{t-1} = i, S_{t-2} = k, \cdots\} = P\{S_t = j | S_{t-1} = i\} = p_{ij}$$

p_{ij} is the transition probability that state j follows state i. We then present the transition matrix as:

$$\mathbf{P} = \begin{bmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{bmatrix}$$

in which $p_{11} + p_{12} = 1$ and $p_{21} + p_{22} = 1$.

3.2.1 Univariate Markov Regime Switching Model

We include the discrete latent state variable S_t in model (1). By applying a univariate Markov regime switching model, we investigate the time series regression of momentum returns as:

$$y_t = \alpha_{S_t} + \sum_{i=1}^{I} \beta_{i,S_t} MacroVariables_{t-1} + \varepsilon_{t,S_t} \qquad (4)$$

In model (4), α_{S_t} and β_{i,S_t} denote the intercept and coefficients of independent variables in state S_t, and ε_{t,S_t} is the regression residual in month t for state S_t. We assume that every coefficient and the residuals variance change with the states.

We extend model (4) by adding risk factors and a proxy for investor sentiment as independent variables:

$$\begin{aligned} MOM_t = \alpha_{S_t} &+ \beta_{1,S_t} DIV_{t-1} + \beta_{2,S_t} TB_{t-1} + \beta_{3,S_t} TERM_{t-1} + \beta_{4,S_t} CRD_{t-1} \\ &+ \beta_{5,S_t} IDPgrowth_{t-1} + \beta_{6,S_t} INF_{t-1} + \beta_{7,S_t} MKT_t + \beta_{8,S_t} SMB_t \\ &+ \beta_{9,S_t} HML_t + \beta_{10,S_t} Liquidity_t + \beta_{11,S_t} CCI_t + \varepsilon_{t,S_t} \qquad (5) \end{aligned}$$

where MKT_t, SMB_t and HML_t are the market factor, the size factor and the value factor in the Fama-French three-factor model in month t, respectively; $Liquidity_t$ is the Pastor-Stambaugh (2003) liquidity factor in month t; CCI_t is the change in the Consumer Confidence Index in month t.

Although we cannot observe the value of S_t directly in month t, we can infer its value according to the observation obtained in month t. The conditional probability that S_t is equal to j is denoted as:

$$\hat{\boldsymbol{\xi}}_{t|t} = P(S_t = j|\Omega_t; \hat{\boldsymbol{\theta}})$$

where $\Omega_t = \{y_t, y_{t-1}, y_{t-2}, \cdots y_0\}$ is the set of observed momentum returns by month t; $\hat{\boldsymbol{\theta}}$ denotes the vector of parameter estimates including all the coefficients, standard deviation of residuals in both states $\sigma_{S_t=1}$ and $\sigma_{S_t=2}$, transition probability p_{11} and p_{22}; and $\hat{\boldsymbol{\xi}}_{t|t}$ is a (2×1) vector for $j = 1$ or 2.

The (2×1) vector of residuals in state 1 and 2 is:

$$\boldsymbol{\eta}_t = \begin{bmatrix} f\left(y_t \middle| S_t = 1, \Omega_{t-1}; \hat{\boldsymbol{\theta}}\right) \\ f\left(y_t \middle| S_t = 2, \Omega_{t-1}; \hat{\boldsymbol{\theta}}\right) \end{bmatrix} = \begin{bmatrix} \dfrac{1}{\sqrt{2\pi}\sigma_{S_t=1}} \exp\left(\dfrac{-(y_t - \mu_{S_t=1})^2}{2{\sigma_{S_t=1}}^2}\right) \\ \dfrac{1}{\sqrt{2\pi}\sigma_{S_t=2}} \exp\left(\dfrac{-(y_t - \mu_{S_t=2})^2}{2{\sigma_{S_t=2}}^2}\right) \end{bmatrix}$$

Here, $\mu_{S_t=1}$ and $\mu_{S_t=2}$ denote the explained portion by independent variables (the fitted value) in regression (3) in state1 and 2 respectively.

We can also make an inference that the process is in state j. We denote conditional probability that S_{t+1} is equal to j as $\hat{\boldsymbol{\xi}}_{t+1|t}$. We can obtain the estimates of parameters $\hat{\boldsymbol{\theta}}$ by the iteration:

$$\hat{\boldsymbol{\xi}}_{t|t} = \frac{(\hat{\boldsymbol{\xi}}_{t|t-1} \odot \boldsymbol{\eta}_t)}{\mathbf{1}'(\hat{\boldsymbol{\xi}}_{t|t-1} \odot \boldsymbol{\eta}_t)}$$

$$\hat{\boldsymbol{\xi}}_{t+1|t} = \mathbf{P} \cdot \hat{\boldsymbol{\xi}}_{t|t}$$

where $\mathbf{P}$ represents the (2×2) transition matrix that governs the state variable S_t, $\mathbf{1}$ denotes (2×1) vector of 1s, and the symbol $\odot$ is an operator which represents element-by-element multiplication.

We use maximum likelihood method to estimate the parameters $\widehat{\boldsymbol{\theta}}$:

$$max\, \mathcal{L}(\widehat{\boldsymbol{\theta}}) = \sum_{t=1}^{T} f\left(y_t \middle| \Omega_{t-1}; \widehat{\boldsymbol{\theta}}\right)$$

where

$$f\left(y_t \middle| \Omega_{t-1}; \widehat{\boldsymbol{\theta}}\right) = \mathbf{1}'(\hat{\boldsymbol{\xi}}_{t|t-1} \odot \boldsymbol{\eta}_t)$$

3.2.2 Multivariate Markov Regime Switching Model

We apply multivariate Markov regime switching regression to jointly model momentum returns and the growth rate of industrial production. The independent variables are the lagged variables including DIV, TB, $TERM$, CRD, INF, and risk factors MKT, SMB, HML, $Liquidity$, as well as proxy for investor sentiment CCI. The developed model is expressed as:

$$\boldsymbol{Y_t} = \begin{bmatrix} MOM_t \\ IDPgrowth_t \end{bmatrix} = \boldsymbol{X\beta} + \begin{bmatrix} \boldsymbol{\varepsilon}_{1t,S_t} \\ \boldsymbol{\varepsilon}_{2t,S_t} \end{bmatrix} \qquad (6)$$

where MOM_t is the momentum return in month t; $IDPgrowth_t$ is the growth rate of industrial production in month t; $\boldsymbol{X}$ is the vector of lagged independent variables including DIV_{t-1}, TB_{t-1}, $TERM_{t-1}$, CRD_{t-1}, INF_{t-1}, risk factors MKT_t, SMB_t, HML_t, $Liquidity_t$, and proxy for investor sentiment CCI_t; $\boldsymbol{\beta}$ is the vector of estimated coefficients; and $(\boldsymbol{\varepsilon}'_{1t,S_t}\boldsymbol{\varepsilon}'_{2t,S_t})' \sim \left(0, \boldsymbol{\Sigma}_{S_t}\right)$ denotes the residual of regression in month t in state S_t.

The vector of residuals in state 1 and 2 becomes:

$$\boldsymbol{\eta}_t = \begin{bmatrix} f(\boldsymbol{Y}_t | S_t = 1, \Omega_{t-1}; \widehat{\boldsymbol{\theta}}) \\ f(\boldsymbol{Y}_t | S_t = 2, \Omega_{t-1}; \widehat{\boldsymbol{\theta}}) \end{bmatrix}$$

$$= \begin{bmatrix} \frac{1}{\sqrt{2\pi}} \boldsymbol{\Sigma}_{S_t=1}{}^{-1} \exp\left[-\frac{1}{2} (\boldsymbol{Y}_t - \widehat{\boldsymbol{\mu}}_{S_t=1}) \boldsymbol{\Sigma}_{S_t=1}{}^{-1} (\boldsymbol{Y}_t - \widehat{\boldsymbol{\mu}}_{S_t=1})' \right] \\ \frac{1}{\sqrt{2\pi}} \boldsymbol{\Sigma}_{S_t=2}{}^{-1} \exp\left[-\frac{1}{2} (\boldsymbol{Y}_t - \widehat{\boldsymbol{\mu}}_{S_t=2}) \boldsymbol{\Sigma}_{S_t=1}{}^{-1} (\boldsymbol{Y}_t - \widehat{\boldsymbol{\mu}}_{S_t=2})' \right] \end{bmatrix}$$

where $\widehat{\boldsymbol{\mu}}_{S_t=1}$ and $\widehat{\boldsymbol{\mu}}_{S_t=2}$ denote vector of the explained portion by independent variables (the fitted value) in regression (3) in state1 and 2 respectively.

We can obtain the estimates of parameters $\widehat{\boldsymbol{\theta}}$ by the iteration:

$$\hat{\boldsymbol{\xi}}_{t|t} = \frac{(\hat{\boldsymbol{\xi}}_{t|t-1} \odot \boldsymbol{\eta}_t)}{\mathbf{1}'(\hat{\boldsymbol{\xi}}_{t|t-1} \odot \boldsymbol{\eta}_t)}$$

$$\hat{\boldsymbol{\xi}}_{t+1|t} = \mathbf{P} \cdot \hat{\boldsymbol{\xi}}_{t|t}$$

where **P** represents the (2×2) transition matrix that governs the state variable S_t, $\mathbf{1}$ denotes (2×1) vector of 1s, and the symbol $\odot$ is an operator which represents element-by element multiplication.

We use maximum likelihood method to estimate the parameters $\widehat{\boldsymbol{\theta}}$:

$$max\, \mathcal{L}(\widehat{\boldsymbol{\theta}}) = \sum_{t=1}^{T} f(\boldsymbol{Y}_t | \Omega_{t-1}; \widehat{\boldsymbol{\theta}})$$

where

$$f(\boldsymbol{Y}_t | \Omega_{t-1}; \widehat{\boldsymbol{\theta}}) = \mathbf{1}'(\hat{\boldsymbol{\xi}}_{t|t-1} \odot \boldsymbol{\eta}_t)$$

3.3. Asset Pricing Tests on Unexplained Portion of Momentum Returns

Fama and French (1996) document that the three-factor model fails to explain the profitability of momentum strategies raised by Jegadeesh and Titman (1993). As a result, momentum factor is added as a fourth risk factor in asset pricing (Carhart (1997)).

We examine whether the pricing capability of momentum is related to macroeconomic variables associated with business cycles and investor sentiment. Our test is based on data from August 1962 to December 2014 due to the availability of the Pastor-Stambaugh (2003) liquidity factor.

The unexplained portion of momentum returns is measured as the residual of the univariate regression (the portion of the momentum returns which cannot be explained by macroeconomic variables, risk factors and proxy for investor sentiment). We define the unexplained portion of momentum as "pure momentum" (PM). We test whether pure momentum (PM) is priced as follows.

First, we run the regression of model (5)

$$\begin{aligned} MOM_t = \alpha_{S_t} &+ \beta_{1,S_t} DIV_{t-1} + \beta_{2,S_t} TB_{t-1} + \beta_{3,S_t} TERM_{t-1} + \beta_{4,S_t} CRD_{t-1} \\ &+ \beta_{5,S_t} IDPgrowth_{t-1} + \beta_{6,S_t} INF_{t-1} + \beta_{7,S_t} MKT_t + \beta_{8,S_t} SMB_t \\ &+ \beta_{9,S_t} HML_t + \beta_{10,S_t} Liquidity_t + \beta_{11,S_t} CCI_t + \varepsilon_{t,S_t} \end{aligned} \quad (5)$$

where MOM_t is the momentum return in month t; DIV_{t-1} is the dividend yield in month $t-1$; TB_{t-1} is the yield on three-month T-bills in month $t-1$; $TERM_{t-1}$ is the term spread in month $t-1$; CRD_{t-1} is the credit spread in month $t-1$; $IDPgrowth_{t-1}$ is the growth rate of Industrial Production in month $t-1$; INF_{t-1} is the inflation rate in month $t-1$; MKT_t, SMB_t and HML_t are the market factor, the size factor and the value factor in the Fama-French three-factor model in month t, respectively; $Liquidity_t$ is the Pastor-Stambaugh (2003) liquidity factor in month t; CCI_t is the change in the Consumer Confidence Index in month t; α_{S_t} and β_{i,S_t} denote intercept in state $S_t$and coefficients of independent variables in state S_t, respectively; ε_{t,S_t} is the residual of regression in month t in state S_t; and I is the number of independent variables.

Second, we measure pure momentum as the unexplained portion (residual) of model (5). Following Hardy, Freeland and Till (2006), we allocate each time period to state 1 or 2 according to the smoothed probability of states obtained from the estimation of model (5). Therefore, we can infer the state for each residual in each month. The series of residuals for each month are given by an indicator function:

$$\varepsilon_t = \varepsilon_{t,S_1} I_{\hat{P}^s_{t,S_1} \geq 0.5} + \varepsilon_{t,S_2}(1 - I_{\hat{P}^s_{t,S_1} \geq 0.5})$$

where $\hat{P}^s_{t,S_1}$ is the smoothed probability of the process belongs to states 1 in month t. We can obtain a $(t \times 1)$ vector of residuals $\boldsymbol{\varepsilon}_t = (\varepsilon_1, \varepsilon_2, \cdots, \varepsilon_t)'$ using this approach.

We then include the vector of $\boldsymbol{\varepsilon}_t$ as the PM factor in a standard asset pricing model at the portfolio level. To examine the pricing capability of pure momentum (PM), we run a time-series regression and a cross-sectional regression.

3.3.1 Time-series Regression for Excess Returns on Portfolios

We run an OLS time-series regression of excess portfolio returns on risk factors and pure momentum (PM) in a factor pricing model

$$R_{it} - R_{ft} = \alpha_i + b_i\left(R_{Mt} - R_{ft}\right) + s_i SMB_t + h_i HML_t + l_i Liquidity_t + p_i PM_t + v_{it} \qquad (7)$$

where R_{it} is the return for portfolio i in month t; R_{ft} is the risk-free rate in month t; R_{Mt} is the market return in month t; SMB_t, HML_t are the size factor and the value factor in the Fama-French three-factor model (Fama and French (1993)) in month t, respectively; $Liquidity_t$ is the Pastor-Stambaugh (2003) liquidity factor in month t; PM_t is the pure momentum we obtained in in month t; α_i is the intercept; b_i, s_i, h_i, l_i, and p_i are the factor loadings; v_{it} is the residual of the regression.

The time-series regression is based on data from August 1962 to December 2014 due to the availability of the Pastor-Stambaugh (2003) liquidity factor. The coefficient estimates and t-statistic of factor loading of PM_t indicates whether PM is statistically significant or not at different levels.

3.3.2 Cross-sectional Regression for Excess Returns on Portfolios

We run a simple cross-sectional regression of average excess returns on factor loadings estimated from the OLS time-series regression:

$$E\left[R_i - R_f\right] = \beta_i \lambda + w_i \qquad (8)$$

where R_i is the return for portfolio i; R_f is the risk-free rate; $E\left[R_i - R_f\right]$ is the estimate of the mean excess return for portfolio i; β_i is the estimates of factor loadings from the time-series regression $R_{it} - R_{ft} = \alpha_i + b_i\left(R_{Mt} - R_{ft}\right) + s_i SMB_t + h_i HML_t + l_i Liquidity_t + p_i PM_t + v_{it}$; λ is the risk premium; w_i is the residual of the regression.

In model (8), we regress estimated mean returns on estimated factor loadings. Therefore, sampling variation of factor loadings affect the covariance matrix of estimates. To account for errors in estimated regressors, we apply the Shanken (1992) correction in estimating the risk premium. The estimates and t-statistic of risk premium indicates the significance of PM at different levels.

4. Data Collection

We use monthly data covering the period between August 1962 and December 2014. Our data is mainly formed into four parts: the first part is momentum returns which reflect the profits to momentum strategies; the second part is macroeconomic variables that are related to the business cycle, which include the dividend yield, the three-month T-bills rate, the term spread, the credit spread, and the growth rate of the industrial production; the third part is market data which includes portfolio returns, market returns, risk free rate, market factor, SMB factor, HML factor, liquidity factor, CRSP Stock Market Indexes, and S&P 500 Index; the fourth part is the Consumer Confidence Index which is included as a proxy for investor sentiment.

In this chapter, we describe our data of momentum returns in section 4.1, the data of macroeconomic variables in section 4.2, the market data in section 4.3, and the Consumer Confidence Index in section 4.4.

4.1. Momentum Returns

We use the monthly momentum factor in Kenneth R. French Data Library[1] as our momentum returns. The momentum returns (MOM) are constructed using returns on six value-weighted portfolios formed monthly on size and the prior 2-12 month returns, which include NYSE, AMEX, and NASDAQ stocks with prior return data. A stock with a price for the end of month $t-13$ and a return for month $t-2$ is eligible to be included in a portfolio for month t. The portfolio construction procedure is as follows. First, all the stocks are sorted by size (market equity) and divided into two portfolios with the breakpoint being the median NYSE market equity. Second, the two portfolios of stocks are re-sorted by prior (2-12) returns and formed into three portfolios within each group as the breakpoints are the 30th and 70th NYSE percentiles. Finally, MOM

[1] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. I thank Professor French for making the data available.

is constructed as the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios.

$$MOM = \frac{1}{2}(Small\ High + Big\ High) - \frac{1}{2}\ (Small\ Low + Big\ Low)$$

We present the summary statistics for the momentum returns in Table 1.

[Please insert Table 1 about here.]

Table 1 shows that from August 1962 to December 2014, momentum returns have an average of 0.6848% and standard deviation of 0.42074‰. The minimum value, maximum value and median of momentum returns are -34.58%, 18.38% and 0.77%, respectively.

Figure 1 demonstrates the time-varying momentum returns.

[Please insert Figure 1 about here.]

The figure shows large fluctuations of momentum returns around the periods 1970-1974, 1980-1981, 1999-2003 and 2007-2009. The fluctuations reflects the effects of realistic economic events to the stock market and general economy, such as the 1970s energy crisis, the early 1980s recession, the information technology bubble, and the financial crisis of 2007-2008. During these periods, the variability of stock market return was extremely high, causing the large variation of profits to momentum strategies.

4.2. Macroeconomic Variables

We use lagged values of macroeconomic variables that are associated to business cycles in our estimation. These macroeconomic variables are dividend yield (DIV), yield on three-month T-bills (TB), term spread (TERM), credit spread (CRD), growth rate of industrial production (IDP growth), and inflation rate (INF). The data set covers the period between April 1953 and December 2014, according to the availability of dividend yield and the yield of Treasury bonds with 10 years to maturity.

We include dividend yield (DIV) as an independent variable in our model. Following Fama and French (1988) and Pontiff and Schall (1998), we compute DIV as total dividend payments accruing to the Center for Research in Security Prices (CRSP) value-weighted index over the previous 12 months divided by the current level of the index. The motivation for using annual dividend yields is to avoid the seasonality of dividend payments. The data of dividend payments and the value-weighted returns are obtained from the Center for Research in Security Prices (CRSP). The yield on three-month T-bills (TB) on the secondary market is included as a proxy for the short-term interest rate. The term spread (TERM) is defined as the difference between the market yield on Treasury bonds with 10 years to maturity and the yield on the three-month T-bills (TB). We define the credit spread (CRD) as the difference between yield on bonds with a Moody's rating of BAA and AAA. The credit spread is commonly named the default spread, which captures the prediction of risk default by the market, and is an indicator of the economic states. Following Fama and French (1988), Pontiff and Schall (1998), and Chordia and Shivakumar (2002), we include these four independent variables above in our models. We also include the growth rate of industrial production (IDP growth), which is an important rate to measure the performance of companies in the industry and the condition of the country's economy. IDP growth rate is continuously compounded, seasonally adjusted and measured as the log difference of the industrial production for major industry groups in the US. We obtain data of yield on three-month T-bills (TB), market yield on Treasury bonds with 10 years to maturity, yield on bonds with a Moody's rating of BAA and AAA, and industrial production from the website of the Board of Governors of the Federal Reserve System[2]. Last but not least, we include inflation rate (INF) as it plays an essential role in determining the health of an economy following Bhar and Malliaris (2011). We measure the inflation rate as the log difference of consumer price index for all urban consumers, all items less food and energy, which is also called core CPI. Consumer price index reflects

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[2] See http://www.federalreserve.gov/releases/h15/data.htg.

consumers' daily living expenses and payments, and core CPI better release underlying price trends (Ang, Bekaert, and Wei (2007)). We obtain data of core consumer price index from the website of Bureau of Labor Statistics[3].

4.3. Market Data

We include a set of risk factors as independent variables for two main reasons. First, we expect that momentum is a risk factor that correlates with economic dynamics, which drive stock prices. Therefore, it is essential to account for the relationship between momentum return and risk premiums such as market premium, size premium, value premium and liquidity premium. Second, market risk factor, size risk factor, value risk factor and liquidity risk factor are confirmed to explain the cross-section of average stock returns, and including these risk factors is broadly applied. As a result, in order to identify the source of the pricing effect of momentum, we include these risk factors to explain momentum returns.

We use a standard asset pricing model to test the pricing capability of pure momentum. We run the test at the monthly portfolio level. We use data from August 1962 to December 2014 due to the availability of the Pastor-Stambaugh (2003) liquidity factor.

We obtain monthly portfolio returns, market returns, risk free rate, MKT (market) factor, SMB (Small Minus Big) factor, HML (High Minus Low) factor from Kenneth R. French Data Library[4]. The monthly portfolios are constructed by double-sorting stocks on size (market equity) and book-to-market equity ratio, which include NYSE, AMEX, and NASDAQ stocks with prior market equity and book equity data. We use

[3] See http://www.bls.gov/cpi/home.htm.

[4] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. I thank Professor French for making the data available.

monthly value weighted returns of the portfolios in the asset pricing tests. We use monthly Pastor-Stambaugh (2003) liquidity factor from Pastor-Stambaugh data library[5].

In order to study the correlation between pure momentum and market return, we obtain value-weighted monthly return and equal-weighted monthly return on CRSP Stock Market Indexes from August 1962 to December 2014. For the CRSP Stock Market Indexes, the market groups of securities include individual NYSE, AMEX, and NASDAQ markets, as well as the NYSE/AMEX and NYSE/AMEX/NASDAQ market combinations. Published S&P 500 and NASDAQ Composite Index Data are also included. In addition, we obtain S&P 500 Index monthly returns from CRSP. They are calculated by (SPINDX(t)/SPINDX(t-1)) – 1, where SPINDX is the level of the Standard & Poor's 500 Composite Index (prior to March 1957, 90-stock index) at the end of the month.

4.4. Investor Sentiment

We use Consumer Confidence Index (CCI) as a proxy for investor sentiment to be included as one of independent variables explaining momentum returns. Defined as the degree of consumers' optimism on the state of the economy, CCI is based on consumers' perceptions of current business and employment conditions, as well as their expectations for six months regarding business conditions, employment and income. CCI is issued each month by the Conference Board on the basis of a household survey of consumers' opinions on current conditions and future expectations of the economy. The index is calculated based on response options including positive, negative or neutral to five questions in the survey, with two questions about opinions on current conditions and three questions about opinions on expectations of future conditions. More specifically, a proportion called a relative value for each question is calculated as the number of positive responses divided by the sum of the number of positive and

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[5] See http://finance.wharton.upenn.edu/~stambaugh/liq_data_1962_2013.txt. We are thankful that Dr. Stambaugh made these data available.

negative responses. Then the relative value for each question is compared against the relative value for the year 1985, which is used as a benchmark. Finally, CCI is measured as the average of the index value for all five questions.

CCI reflects consumers' confidence with respect to the current economy and their expectations for the immediate future. Therefore, CCI could imply the condition of economic growth from the perspective of the consumer. Increasing consumer confidence indicates that consumers are more confident about the economy and their jobs and incomes, therefore they are more likely to spend more money to make purchases, resulting a higher consumption and economic growth. A number of papers use CCI as an indicator of countries' economic health and an informative forecasting tool that has predicting power (Acemoglu and Scott (1994), Bram and Ludvigson (1998), Ferrer, Salaber, and Zalewska (2016)) and more recently, Lemmon and Portniaguina (2006), Fisher and Statman (2003), Jansen and Nahuis (2003), Schmeling (2009), Bathia and Bredin (2013), Kalotay, Gray, and Sin (2007), Zouaoui, Nouyrigat, and Beer (2011). As a result, we also include CCI as a proxy for investor sentiment.

We use the change of CCI by taking the first log difference of the Consumer Confidence Index.

Table 2 presents the correlation between momentum returns and explanatory variables.

[Please insert Table 2 about here.]

Table 2 show that dividend yield is significantly and positively correlated to T-bills rate, credit spread and inflation rate, whereas significantly and negatively correlated to term spread and IDP growth rate; T-bills rate is significantly and negatively correlated to term spread; credit spread is significantly and positively correlated to T-bills rate, term spread and inflation rate, but significantly, negatively correlated to IDP growth rate; inflation rate is significantly and positively correlated to T-bills rate, whereas significantly and negatively correlated to term spread. We find that dividend yield and inflation rate have significant correlation with all the other macroeconomic variables, which indicates that dividend yield could be attributed to the other variables. Moreover, we find that correlations between inflation rate and market premium is negative and significant; liquidity premium is significantly correlated to all the other variables and factors. In addition, Consumer Confidence Index is significantly correlated to T-bills rate, term spread, credit spread, inflation rate, market, size and liquidity risk premiums, which indicates that Consumer Confidence Index is an efficient and essential barometer of countries' economy to monitor general future economic situation. As a result, we infer that Consumer Confidence Index could play an important role explaining profitability of momentum strategies.

5. Empirical findings

In section 5.1, we present the results of unconditional ordinary linear regressions, and in section 5.2, the results of univariate and multivariate Markov regime switching regressions. In section 5.3, we report the results of asset pricing tests on the pricing capability of unexplained portion of momentum returns.

5.1. Ordinary Linear Regression of Momentum Returns

First, we run an ordinary linear (OLS) regression of momentum returns on lagged macroeconomic variables, risk factors and proxy for investor sentiment.

$$MOM_t = \alpha + \beta_1 DIV_{t-1} + \beta_2 TB_{t-1} + \beta_3 TERM_{t-1} + \beta_4 CRD_{t-1} + \beta_5 IDPgrowth_{t-1} + \beta_6 INF_{t-1} + \beta_7 MKT_t + \beta_8 SMB_t + \beta_9 HML_t + \beta_{10} Liquidity_t + \beta_{11} CCI_t + \varepsilon_t \quad (3)$$

The results are reported in Table 3.

[Please insert Table 3 about here.]

From Table 3, we find significant positive relation between momentum returns and T-bill rate, which indicates that short-term rates reflect future economy activity. Term (credit) spread is significantly and positively (negatively) related to momentum returns. Since a wide credit spread implies a slowing economy, it can influence the momentum returns as a proxy for economy growth. The risk factors, MKT, SMB and HML are all significantly, negatively related to momentum returns, but liquidity is significantly, positively related, which indicates that all the risk factors play important roles explaining momentum returns. Moreover, Consumer Confidence Index is significantly and negatively related to momentum returns, which is consistent with the findings of Baker and Wurgler (2006).[6]

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[6] In addition to the log difference of CCI in month t and month t-1, we also estimate the model using the log difference of CCI in month t and month t-2, t-3, t-6, and t-12. The coefficients of other measures are all not statistically significant. The adjusted R^2 of the models with the log difference of CCI in month t and month t-2, t-3,

As shown in Table 3, the adjusted R^2 is around 1 percent to 6 percent. Our findings are consistent with the findings of Chordia and Shivakumar (2002) who report an adjusted R^2 of -0.02 to 0.10 when regressing momentum strategy payoffs on macroeconomic predictor variables including dividend yield, default spread, term spread, and T-bills rate for each five-year sub-period.[7]

5.2. Markov Regime Switching Regression of Momentum Returns

5.2.1 Univariate Markov Regime Switching Regression of Momentum Returns

We propose two-state univariate Markov regime switching regressions of momentum returns on macroeconomic variables, risk factors and proxy for investor sentiment. Figure 2 describes the smoothed probability of states inferred by the two-state univariate Markov regime switching regression model

$$\begin{aligned} MOM_t = \alpha_{S_t} &+ \beta_{1,S_t} DIV_{t-1} + \beta_{2,S_t} TB_{t-1} + \beta_{3,S_t} TERM_{t-1} + \beta_{4,S_t} CRD_{t-1} \\ &+ \beta_{5,S_t} IDPgrowth_{t-1} + \beta_{6,S_t} INF_{t-1} + \beta_{7,S_t} MKT_t + \beta_{8,S_t} SMB_t \\ &+ \beta_{9,S_t} HML_t + \beta_{10,S_t} Liquidity_t + \beta_{11,S_t} CCI_t + \varepsilon_{t,S_t} \qquad (5) \end{aligned}$$

[Please insert Figure 2 about here.]

This figure covers the period August 1962 to December 2014. In figure 2, state 1 is identified as a relatively low-volatility regime and state 2 as a high-volatility regime.[8] We find that the smoothed probability of state 1 is extremely low around the periods

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t-6, and t-12 are 0.0650, 0.0641, 0.0646, and 0.0646, respectively. Our results show that the model with first log difference of CCI dominates the models with other measures. The results are available upon request.

[7] In comparison, Chordia and Shivakumar (2002) report an adjusted R^2 of 6 percent when portfolio returns are regressed on macroeconomic variables; Pontiff and Schall (1998) report an adjusted R^2 of 7 percent when the CRSP value-weighted market return is the dependent variable and 9 percent when the equal-weighted market return is the dependent variable.

[8] States are classified by residual variances. In full model, residual variance of state 1 is 4.0251 and state 2 is 37.1715. Based on the diagonal elements of the transition probability matrix, probability of state 1 and state 2 to persist are 0.96 and 0.93, which indicates that the low-volatility regime (state 1) is more likely to persist.

1973-1974, 1980-1981, 1998-2002 and 2007-2008 during last five decades. Contraction happens during these time spans results from the 1970s energy crisis, the early 1980s recession, the information technology bubble, and the global financial crisis of 2008. Therefore, we identify state 1 as an expansion state and state 2 as a contraction state.

Table 4 presents coefficient estimates of two-state univariate Markov regime switching regressions.

[Please insert Table 4 about here.]

In Table 4, we report *t*-statistics in parentheses to show the significance of coefficients. In addition, we apply Wald tests for the equality of the parameters across the two regimes. We report p-values of Wald tests in brackets. The last column includes adjusted McFadden's Pseudo R^2 for each model.

On the one hand, in terms of low-volatility regime (state 1), T-bills rate, term spread and IDP growth are significantly and positively related to momentum returns through a two-state univariate Markov regime switching approach. Credit spread is significantly and negatively related to momentum returns, which is consistent with the results of OLS model. However, dividend yield and inflation rate seem to lose their explanatory power. In case of risk factors, MKT and SMB are significantly and negatively related to momentum returns, which is consistent with our previous results. Moreover, Consumer Confidence Index is significantly and negatively related to momentum returns, which is consistent with the findings of Baker and Wurgler (2006).[9]

On the other hand, in high-volatility regime (state 2), most of the independent variables lose their explanatory power except for credit spread, market factor and size factor. Furthermore, Mishkin (2010) has argued that periods with high volatility are

[9] In addition to the log difference of CCI in month t and month t-1, we also estimate the model using the log difference of CCI in month t and month t-2, t-3, t-6, and t-12. The adjusted McFadden's Pseudo R^2 for these models are 0.0132, 0.0117, 0.0148, and 0.0110, respectively. The results are available upon request.

often related to turning points in business cycles. Therefore, the duration of these kinds of periods are usually brief. During these periods, it is not easy to explain these turning points using consistent economic variables. Our results significantly capture these features of high-volatility regime[10].

Table 4 also presents test statistics for the equality of the parameters across the two regimes. The results of Wald tests show that the coefficients of credit spread, IDP growth, MKT, SMB and liquidity factors are significantly different across the two states.

However, the adjusted McFadden's Pseudo R^2 of 0.0078 for the full model (8) indicates low explanatory power of our model. Macroeconomic variables, risk factors and proxy for investor sentiment cannot fully explain momentum returns. In other words, macroeconomic variables, risk factors and proxy for investor sentiment only explain a small portion of the profitability of momentum strategies.

5.2.2 Multivariate Markov Regime Switching Regression of Momentum Returns

We extent the univariate Markov regime switching model into multivariate model to examine whether momentum returns and IDP growth rate are jointly related to macroeconomic variables and investor sentiment. Figure 3 describes the smoothed probability of states estimated by the model

$$\boldsymbol{Y_t} = \begin{bmatrix} MOM_t \\ IDPgrowth_t \end{bmatrix} = \boldsymbol{X\beta} + \begin{bmatrix} \boldsymbol{\varepsilon}_{1t,S_t} \\ \boldsymbol{\varepsilon}_{2t,S_t} \end{bmatrix} \qquad (6)$$

[Please insert Figure 3 about here.]

In figure 3, state 1 is identified as a relatively low-volatility regime and state 2 as a high-volatility regime. We find that the smoothed probability of state 1 is extremely

[10] Bhar and Malliaris (2011) have documented that state with high volatility tends to have shorter expected duration and state with low volatility tends to have longer expected duration. According to our results, the average duration of low-volatility regime is 24.87 months, whereas the average duration of high-volatility regime is 13.35 months, consistent with Bhar and Malliaris (2011).

low around the periods 1973-1974, 1980-1981, 1999-2003 and 2008-2009 in the past five decades. Similar to the results of univariate Markov regime switching model, contraction happens during these time spans results from the 1970s energy crisis, the early 1980s recession, the information technology bubble, and the global financial crisis of 2008. Similarly, we identify state 1 as an expansion state and state 2 as a contraction state.

Table 5 presents estimation results of two-state multivariate Markov regime switching regression.

[Please insert Table 5 about here.]

In Table 5, we report *t*-statistics in parentheses to show the significance of parameter estimates. σ^2 denotes the percentage of variance of residuals of the regression. The last row includes adjusted McFadden's Pseudo R^2 for each model.

Table 5 shows that T-bills rate and liquidity factor are significantly and positively related to momentum returns, whereas credit spread, MKT factor, HML factor and CCI are significantly and negatively related to momentum returns in the low-volatility regime (state 1). However, in the high-volatility regime (state 2), none of the explanatory variables are statistically significantly related to momentum returns. Among all the macroeconomic variables, T-bills rate, term spread and credit spread are significantly related to IDP growth.

The variance of residuals show again that state 1 is characterized as a relatively low-volatility regime and state 2 as a high-volatility regime.[11] We report covariance matrix of errors from two-state multivariate Markov regime switching regression in Table 6.

[11] The expected duration of low-volatility regime is 40.19 months, whereas the average duration of high-volatility regime is 6.84 months, consistent with our analysis of univariate Markov regime switching model. Based on the diagonal elements of the transition probability matrix, probability of low-volatility regime and high-volatility regime to persist are 0.98 and 0.85, which indicates that the low-volatility regime (state 1) is more likely to persist.

[Please insert Table 6 about here.]

However, similar to the results of univariate Markov regime switching model, the adjusted McFadden's Pseudo R^2 of 0.0032 indicates low explanatory power for the multivariate model (6). In a framework of multivariate Markov regime switching model, macroeconomic variables, risk factors and proxy for investor sentiment only explain a small portion of the profitability of momentum strategies.

5.3. Asset Pricing Tests on Unexplained Portion of Momentum Returns

We measure the momentum (PM) as the unexplained portion (residual) of model (5). Following Hardy, Freeland and Till (2006), we obtain the series of residuals for each month by an indicator function:

$$\varepsilon_t = \varepsilon_{t,S_1} I_{\hat{P}^s_{t,S_1} \geq 0.5} + \varepsilon_{t,S_2}(1 - I_{\hat{P}^s_{t,S_1} \geq 0.5})$$

where $\hat{P}^s_{t,S_1}$ is the smoothed probability of the process belongs to low-volatility regime (states 1) in month t. The indicator approach is identical to a zero-one weighting.

Figure 4 demonstrates both the smoothed probability of low-volatility regime (state 1) and the time-varying indicator $I_{\hat{P}^s_{t,S_1} \geq 0.5}$.

[Please insert Figure 4 about here.]

In order to compare residuals generated by the two different approaches documented by Hardy, Freeland and Till (2006), we plot both weighted residuals and indicator residuals in figure 5.

[Please insert Figure 5 about here.]

The weighted residuals are calculated as the weighted average of the two residuals from tow regimes using the conditional probability for each regime. The smoothed state probabilities of state 1 and state 2 are inferred by two-state univariate Markov regime switching regression. This figure covers the period August 1962 to December 2014. In this figure, solid line is the weighted residuals, and dashed line is the indicator residuals. Figure 5 demonstrates very similar time-varying weighted residuals and indicator residuals.

We present the summary statistics for the pure momentum in Table 7.

[Please insert Table 7 about here.]

Table 7 shows that from August 1962 to December 2014, pure momentum has an average of 0.0361% and standard deviation of 0.3870‰. The minimum value, maximum value and median of pure momentum returns are -26.9278%, 18.1440% and 0.1378%, respectively. Table 7 also shows the summary statistics for the pure momentum from state 1 and state 2.

Moreover, we investigate the correlation between pure momentum and market returns. We calculate the correlations between monthly pure momentum and CRSP Stock Market Indexes (both value-weighted and equal-weighted), S&P 500 Index monthly return, and 25 portfolios based on size and book-to-market ratio monthly return, separately. Table 8 reports the results.

[Please insert Table 8 about here.]

Panel A of Table 8 describes that monthly pure momentum is strongly and negatively correlated to equal-weighted CRSP Stock Market Indexes and S&P 500 Index monthly return with correlation of -0.1364 and -0.0883, respectively. Panel B and C of Table 8 shows the negative correlation between pure momentum and return on portfolios. High correlation between pure momentum and return of market index indicates that pure momentum contains a large amount of information of stock market return realized in the same period, and pure momentum could be a priced factor explaining excess stock returns.

To examine the pricing capability of pure momentum (PM), we run a time-series regression of portfolio returns and a cross-sectional regression on Fama-French three factors, liquidity factor and pure momentum (PM).

5.3.1 Time-series Regression for Excess Returns on Portfolios

First, we conduct a time-series regression of portfolio returns on Fama-French three factors, liquidity factor and pure momentum (PM), in order to determine if pure momentum is priced. If pure momentum is not priced, the pricing effect of momentum returns are entirely explained by the selected macroeconomic variables, risk factors and proxy for investor sentiment. Table 9 reports the regression results.

[Please insert Table 9 about here.]

Table 9 presents coefficients estimates, t-statistic of factor loadings, adjusted R^2 and standard error of residuals for time-series regression. Following Fama and French (1996), we find MKT, SMB, HML and liquidity factors all help explain excess portfolio return. The model has an average adjusted R^2 of 0.87 and an average standard error of residuals of 1.94.

Table 9 shows that 17 out of 25 coefficients of pure momentum are statistically significantly different from zero.[12] The result implies that pure momentum has pricing effect on portfolio returns as a risk premium. Since we adjust the momentum returns by macroeconomic variables, risk factors and proxy for investor sentiment, the pure momentum is the portion which cannot be explained by the independent variables. The result of time-series regression on pure momentum shows that the pricing capability of momentum cannot be entirely explained by macroeconomic variables, risk factors and proxy for investor sentiment, which is consistent with our main results.

[12] We use number of IPOs and the first log difference of New Orders Index from Institute for Supply Management Manufacturing as alternatives to CCI. Asset pricing tests show similar results. Number of coefficients that are statistically significantly different from zero are respectively 5 and 3 out of 25 in time-series regression.

5.3.2 Cross-sectional Regression for Excess Returns on Portfolios

To assess the pricing effects of pure momentum, we also conduct a cross-sectional regression of portfolio returns on Fama-French three factors, liquidity factor and pure momentum (PM). We regress mean of return on estimated factor loadings obtained from the previous time-series regression. We apply Shanken (1992) correction for the t-statistic of the risk premium. If risk premium on pure momentum is not priced, the pricing effect of momentum returns are entirely explained by the selected macroeconomic variables, risk factors and proxy for investor sentiment. Table 10 reports the regression results.

[Please insert Table 10 about here.]

Table 10 presents the estimates of factor risk premiums, t-statistic of factor risk premiums and the pricing errors of cross-sectional regression. We find risk premium on MKT, HML and liquidity factors are significant different from zero, indicating these risk factors help explain excess portfolio return. The model has an adjusted R^2 of 0.69.

Panel A of Table 10 shows that estimate of risk premium on pure momentum is statistically significantly different from zero at 10% level.[13] The t-statistic of risk premium on pure momentum is 1.79. Panel B of Table 10 shows that the pricing error of the cross-sectional model is small since only 3 out of 25 pricing errors are statistically significantly different from zero. This result shows that pure momentum has pricing capability explaining excess portfolio returns, in other words, the pricing capability of momentum cannot be entirely explained by macroeconomic variables, risk factors and proxy for investor sentiment, which is consistent with our main results.

[13] We use number of IPOs and the first log difference of New Orders Index from Institute for Supply Management Manufacturing as alternatives to CCI. Asset pricing tests show similar results. Estimates of risk premium on pure momentum is statistically significantly different from zero at 5% and 1% level in cross-sectional regression. The t-statistic of risk premium on pure momentum is 2.05 and 2.59, respectively.

6. Conclusions

As the only remaining CAPM-related anomaly unexplained by the Fama-French three-factor model, the profitability of momentum strategies has been intriguing interests of many researchers during the last two decades. Since the publication of the study by Jegadeesh and Titman (1993), a number of theoretical and empirical studies have examined the existence of momentum anomaly and provided explanations for momentum profits. There are mainly two categories of explanations for the momentum anomaly among academics. The first is behavioral explanation, in which momentum anomaly is attributed to investors' sentiment to news and events. The other explanation for the momentum anomaly is based on concepts of risk. A growing body of studies have investigated the relationship between momentum anomaly and economic dynamics and investor sentiment.

However, to our knowledge, previous literature did not address the effects of macroeconomic risk factors and investor sentiment on pricing capability of momentum factor. Moreover, we find very few studies that discuss the momentum returns under a Markov regime switching framework of Hamilton (1989) which captures the dynamic behaviors of the economic time series through different regimes.

This thesis explore the relationship between the profitability of momentum strategies and macroeconomic variables associated with the business cycles as well as investor sentiment for the period August 1962 to December 2014. First, we apply a two-state univariate Markov regime switching model to describe momentum returns. We identify state 1 as an expansion state and state 2 as a contraction state according to the estimates of smoothed probabilities in the regime switching model. We find that macroeconomic variables, risk factors and proxy for investor sentiment show explanatory power for momentum returns, whereas the explanatory power is not strong to fully explain the momentum profits. Second, we evaluate the explanatory power of macroeconomic variables, risk factors and proxy for investor sentiment using a two-state multivariate Markov regime switching model which accounts for the correlation of jointly distributed momentum return series and industrial production growth. We find similar results as the univariate model that macroeconomic variables, risk factors and proxy for investor sentiment only explain a small portion of the profitability of momentum strategies. Our results confirm the findings of Liew and Vassalou (2000), Cooper, Gutierrez, and Hammed (2004), Griffin, Ji, and Martin (2003), and Antoniou, Lam, and Paudyal (2007).

We define the unexplained portion of momentum returns as pure momentum, which is measured as the residual of the univariate regression. Following Hardy, Freeland and Till (2006), we estimate pure momentum using indicator approach which is identical to a zero-one weighting according to the smoothed probability of states obtained from estimates of smoothed probabilities in the regime switching model. Using monthly return on portfolios constructed by double-sorting stocks on size (market equity) and book-to-market equity ratio, which include NYSE, AMEX, and NASDAQ stocks, we apply time-series and cross-sectional asset pricing test to investigate the pricing capability of pure momentum. The results of time-series regression show that from August 1962 to December 2014, in the case of 17 out of 25 portfolios, coefficients of pure momentum are statistically significantly different from zero. The result implies that pure momentum has pricing effect on portfolio returns as a risk premium. As a result, the pricing capability of momentum cannot be entirely explained by macroeconomic variables, risk factors and proxy for investor sentiment. The results of cross-sectional regression show that estimate of risk premium on pure momentum is statistically significantly different from zero at 10% level which indicates that pure momentum has pricing capability explaining excess portfolio returns. The results of asset pricing are consistent with our main results obtained from regime switching model.

This thesis contributes to the literature in several aspects. First, it investigates relationship between profitability of momentum strategies and macroeconomic variables associated with the business cycles as well as investor sentiment using various specifications of Markov regime switching model to obtain more information and inferences provided by time series of momentum returns. Second, it explores the impacts of macroeconomic variables and investor sentiment on the pricing effect of momentum factor by testing pricing capability of pure momentum adjusted by explanatory variables. Third, it apply multivariate Markov regime switching regression to jointly model momentum returns and the growth rate of industrial production in order to capture the correlation of jointly distributed series.

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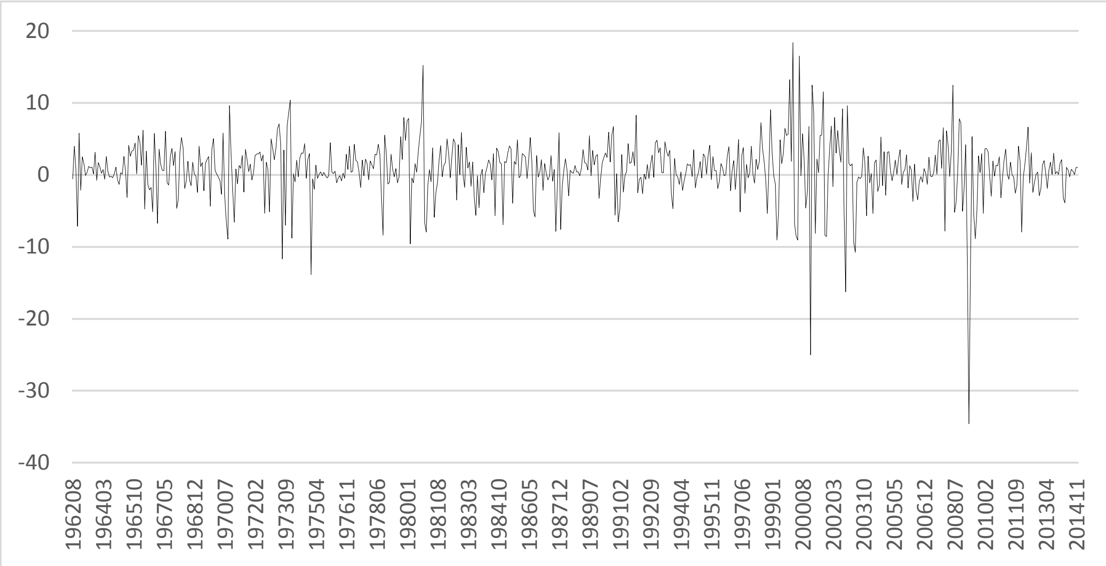
Figure 1: Time-varying Monthly Momentum Returns

This figure demonstrates the time variation of the monthly momentum returns reported in Kenneth R. French Data Library[14] for the period August 1962 to December 2014. The momentum returns are constructed using returns on six value-weighted portfolios monthly formed on size and prior (2-12) returns, which include NYSE, AMEX, and NASDAQ stocks with prior return data. The sample includes data of 629 months.



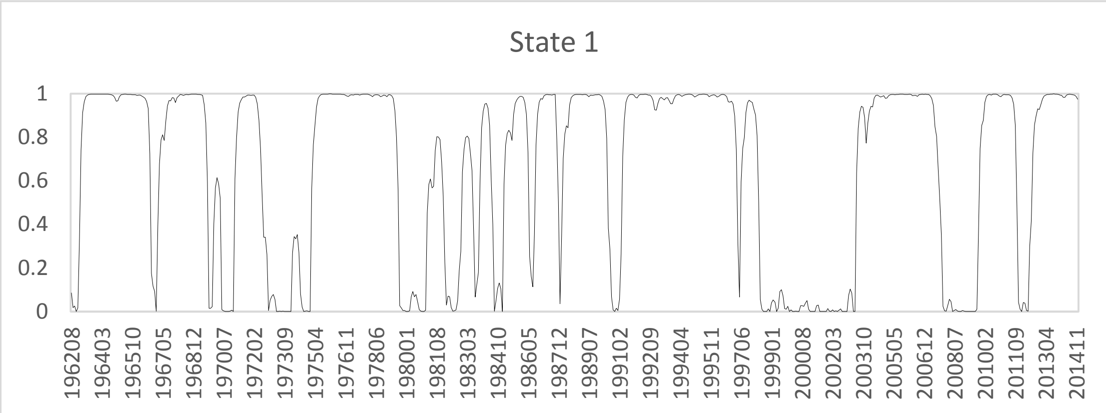
[14] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. I thank Professor French for making the data available.

Figure 2: Smoothed State Probabilities Inferred by Two-state Univariate Markov Regime Switching Regression

This figure describes the smoothed state probabilities inferred by two-state univariate Markov regime switching regression

$$
\begin{aligned}
MOM_t = \alpha_{S_t} + \beta_{1,S_t} DIV_{t-1} + \beta_{2,S_t} TB_{t-1} + \beta_{3,S_t} TERM_{t-1} + \beta_{4,S_t} CRD_{t-1} + \beta_{5,S_t} IDPgrowth_{t-1} \\
+ \beta_{6,S_t} INF_{t-1} + \beta_{7,S_t} MKT_t + \beta_{8,S_t} SMB_t + \beta_{9,S_t} HML_t + \beta_{10,S_t} Liquidity_t \\
+ \beta_{11,S_t} CCI_t + \varepsilon_{t,S_t}
\end{aligned}
$$

where MOM_t is the momentum return in month t; DIV_{t-1} is the dividend yield in month $t-1$; TB_{t-1} is the yield on three-month T-bills in month $t-1$; $TERM_{t-1}$ is the term spread in month $t-1$; CRD_{t-1} is the credit spread in month $t-1$; $IDPgrowth_{t-1}$ is the growth rate of industrial production in month $t-1$; INF_{t-1} is the inflation rate in month $t-1$; MKT_t, SMB_t and HML_t are the market factor, the size factor and the value factor in the Fama-French three-factor model in month t, respectively; $Liquidity_t$ is the Pastor-Stambaugh (2003) liquidity factor in month t; CCI_t is the change in the Consumer Confidence Index in month t. α_{S_t} and β_{i,S_t} denote intercept in state S_t and coefficients of independent variables in state S_t, respectively; ε_{t,S_t} is the residual of regression in month t in state S_t. We identify state 1 as an expansion state and state 2 as a contraction state. The figure covers the period August 1962 to December 2014.



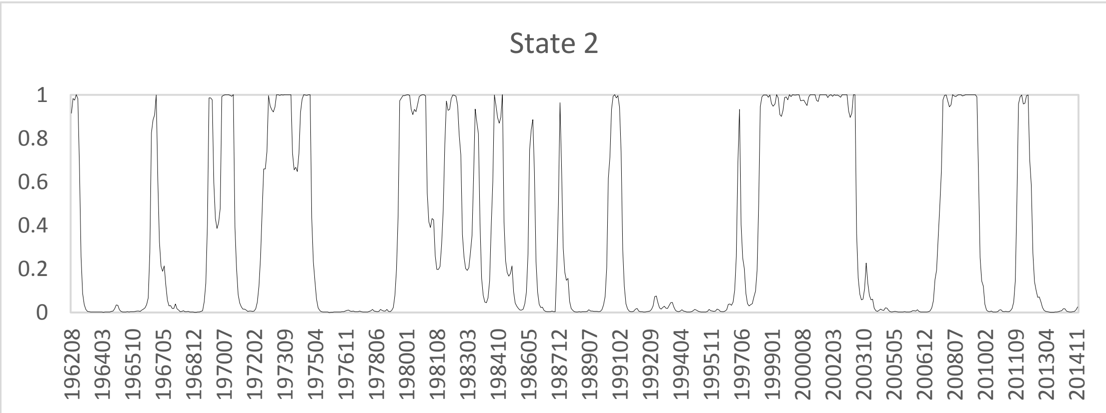
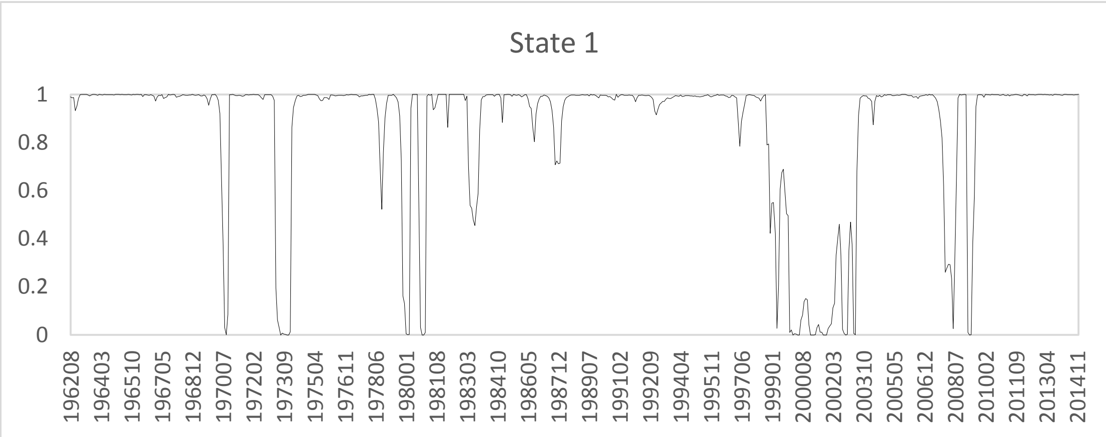


Figure 3: Smoothed State Probabilities Inferred by Two-state Multivariate Markov Regime Switching Regression

This figure describes the smoothed state probabilities inferred by two-state multivariate Markov regime switching regression

$$\boldsymbol{Y_t} = \begin{bmatrix} MOM_t \\ IDPgrowth_t \end{bmatrix} = \boldsymbol{X\beta} + \begin{bmatrix} \boldsymbol{\varepsilon}_{1t,S_t} \\ \boldsymbol{\varepsilon}_{2t,S_t} \end{bmatrix}$$

where MOM_t is the momentum return in month t; $IDPgrowth_t$ is the growth rate of industrial production in month t; $\boldsymbol{X}$ is the vector of lagged independent variables including DIV_{t-1}, TB_{t-1}, $TERM_{t-1}$, and CRD_{t-1}, risk factors including MKT_t, SMB_t, HML_t, and $Liquidity_t$, and the change in the Consumer Confidence Index CCI_t. $\boldsymbol{\beta}$ is the vector of estimated coefficients; and $(\boldsymbol{\varepsilon}'_{1t,S_t}\boldsymbol{\varepsilon}'_{2t,S_t})' \sim (0, \boldsymbol{\Sigma}_{S_t})$ denotes the residual of regression in month t in state S_t. We identify state 1 as an expansion state and state 2 as a contraction state. The figure covers the period August 1962 to December 2014.



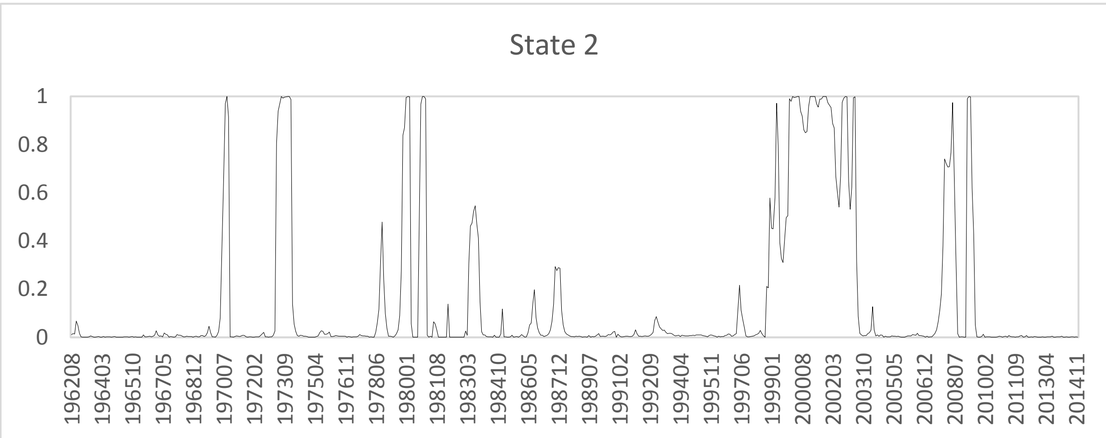


Figure 4: Smoothed Probabilities of State 1 and Time-varying Indicator Inferred by Two-state Univariate Markov Regime Switching Regression

This figure demonstrates both the smoothed probability of state 1 and the time-varying indicator $I_{\hat{P}^s_{t,S_1} \geq 0.5}$. The smoothed probability of state 1 is inferred by two-state univariate Markov regime switching regression

$$MOM_t = \alpha_{S_t} + \beta_{1,S_t} DIV_{t-1} + \beta_{2,S_t} TB_{t-1} + \beta_{3,S_t} TERM_{t-1} + \beta_{4,S_t} CRD_{t-1} + \beta_{5,S_t} IDPgrowth_{t-1} + \beta_{6,S_t} INF_{t-1} + \beta_{7,S_t} MKT_t + \beta_{8,S_t} SMB_t + \beta_{9,S_t} HML_t + \beta_{10,S_t} Liquidity_t + \beta_{11,S_t} CCI_t + \varepsilon_{t,S_t}$$

where MOM_t is the momentum return in month t; DIV_{t-1} is the dividend yield in month $t-1$; TB_{t-1} is the yield on three-month T-bills in month $t-1$; $TERM_{t-1}$ is the term spread in month $t-1$; CRD_{t-1} is the credit spread in month $t-1$; $IDPgrowth_{t-1}$ is the growth rate of industrial production in month $t-1$; INF_{t-1} is the inflation rate in month $t-1$; MKT_t, SMB_t and HML_t are the market factor, the size factor and the value factor in the Fama-French three-factor model in month t, respectively; $Liquidity_t$ is the Pastor-Stambaugh (2003) liquidity factor in month t; CCI_t is the change in the Consumer Confidence Index in month t. α_{S_t} and β_{i,S_t} denote intercept in state S_t and coefficients of independent variables in state S_t, respectively; ε_{t,S_t} is the residual of regression in month t in state S_t. The figure covers the period August 1962 to December 2014. We identify state 1 as an expansion state and state 2 as a contraction state. Dashed line is the smoothed probability of state 1. Solid line is the indicator $I_{\hat{P}^s_{t,S_1} \geq 0.5}$.

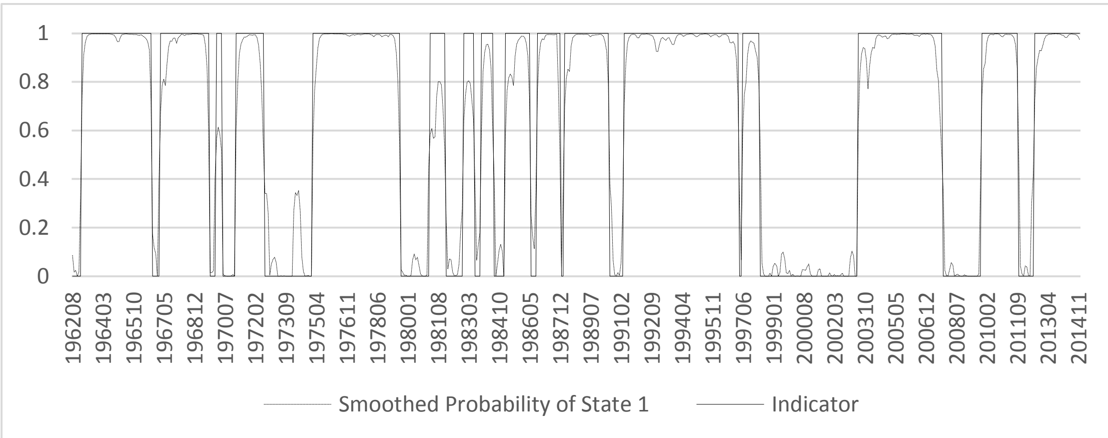


Figure 5: Weighted and Indicator Residuals Inferred by Two-state Univariate Markov Regime Switching Regression

This figure demonstrates residuals generated by two different approaches. The weighted residuals are calculated as the weighted average of the two residuals from tow regimes using the conditional probability for each regime. The indicator residuals are given by an indicator function

$\varepsilon_t = \varepsilon_{t,S_1} I_{\hat{P}^s_{t,S_1} \geq 0.5} + \varepsilon_{t,S_2}(1 - I_{\hat{P}^s_{t,S_1} \geq 0.5})$ where $\hat{P}^s_{t,S_1}$ is the smoothed probability of the process belongs to states 1 in month t. The indicator approach is identical to a zero-one weighting. The indicator residuals are named as pure momentum. The smoothed state probabilities of state 1 and state 2 are inferred by two-state univariate Markov regime switching regression:

$$MOM_t = \alpha_{S_t} + \beta_{1,S_t} DIV_{t-1} + \beta_{2,S_t} TB_{t-1} + \beta_{3,S_t} TERM_{t-1} + \beta_{4,S_t} CRD_{t-1} + \beta_{5,S_t} IDPgrowth_{t-1} + \beta_{6,S_t} INF_{t-1} + \beta_{7,S_t} MKT_t + \beta_{8,S_t} SMB_t + \beta_{9,S_t} HML_t + \beta_{10,S_t} Liquidity_t + \beta_{11,S_t} CCI_t + \varepsilon_{t,S_t}.$$

We identify state 1 as an expansion state and state 2 as a contraction state. The figure covers the period August 1962 to December 2014. Solid line is the weighted residuals. Dashed line is the indicator residuals.

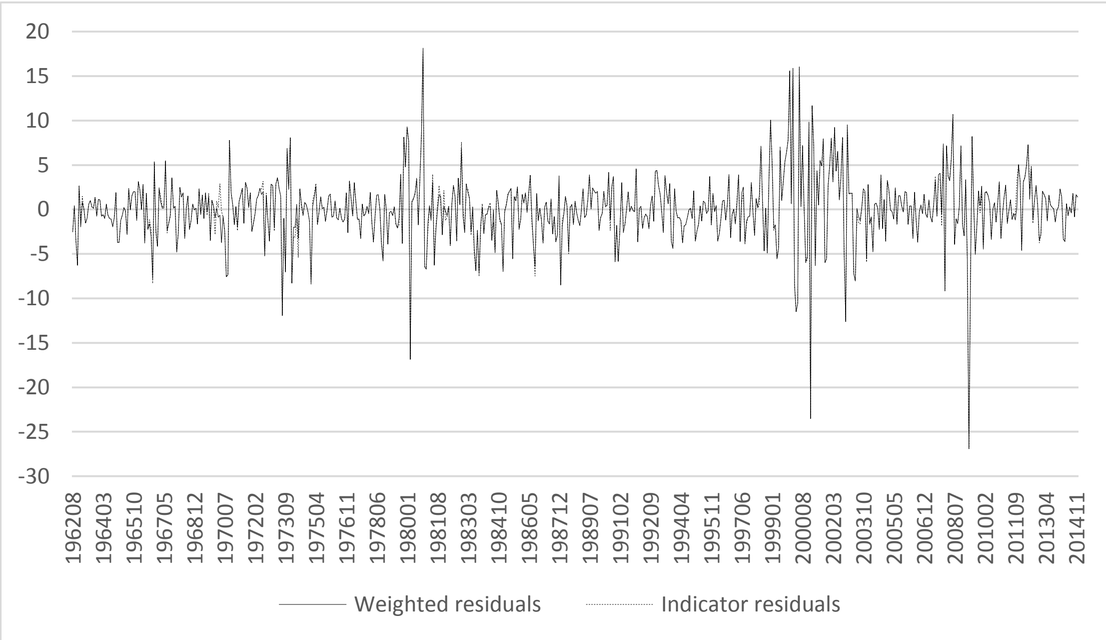


Table 1: Summary Statistics for Monthly Momentum Returns

This table presents summary statistics for the monthly momentum returns reported in Kenneth R. French Data Library for the period August 1962 to December 2014. The momentum returns are constructed using returns on six value-weighted portfolios monthly formed on size and prior (2-12) returns, which include NYSE, AMEX, and NASDAQ stocks with prior return data. The sample includes data of 629 months.

	Mean (%)	Standard deviation (‰)	Min (%)	Max (%)	Median (%)
Momentum returns	0.6848	0.42074	-34.58	18.38	0.77

Table 2: Correlations across Momentum Returns, Macroeconomic Variables, Risk Factors and Proxy for Investor Sentiment

This table presents correlation coefficients across momentum returns, macroeconomic variables, risk factors and proxy for investor sentiment during the period August 1962 to December 2014. DIV is the dividend yield, i.e., total dividend payments accruing to the Center for Research in Security Prices (CRSP) value-weighted index over the previous 12 months divided by the current level of the index (Pontiff and Schall (1998)). TB denotes the three-month T-bills rate. TERM is term spread, i.e., the difference between the market yield on Treasury bonds with 10 years to maturity and the yield on the three-month T-bills (TB). CRD (credit) stands for the difference between yield on bonds with a Moody's rating of BAA and the yield on bonds rated AAA by Moody's. IDP growth rate is continuously compounded, seasonally adjusted and measured as the log difference of the industrial production (IDP). INF (inflation) stands for the inflation rate, i.e., the log difference of the consumer price index for all urban consumers, all items less food and energy. The CPI is seasonally adjusted and obtained from the Bureau of Labor Statistics website[15]. MKT is the difference between the market return and the risk-free rate. MKT, SMB and HML are the market factor, the size factor and the value factor in the Fama-French three-factor model (Fama and French (1993)), respectively. Liquidity is the Pastor-Stambaugh (2003) liquidity factor. CCI is the change in the Consumer Confidence Index by taking the first log difference of the Consumer Confidence Index from OECD Data. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	MOM	DIV	TB	TERM	CRD	IDP growth	INF	MKT	SMB	HML	Liquidity	CCI
MOM	1.0000											
DIV	-0.0098	1.0000										
TB	0.0643	0.6846***	1.0000									
TERM	-0.0219	-0.1132***	-0.4717***	1.0000								
CRD	-0.1204***	0.4363***	0.2559***	0.2574***	1.0000							
IDP growth	0.0826**	-0.1222***	-0.0614	0.0434	-0.3368***	1.0000						
INF	0.0467	0.6311***	0.6631***	-0.3436***	0.2194***	-0.0751*	1.0000					
MKT	-0.1328***	0.0558	-0.0681*	0.0832**	0.0538	0.0376	-0.1066***	1.0000				
SMB	-0.1570***	0.1092***	-0.0443	0.0571	0.1079***	-0.04033	-0.0040	0.2856***	1.0000			
HML	-0.0521	-0.0512	0.0684*	-0.0397	-0.0656*	0.0258	0.0558	-0.2790***	-0.2274***	1.0000		
Liquidity	0.0377	-0.0704*	-0.1002**	0.1260***	-0.0862**	0.1227***	-0.1611***	0.2834***	0.1714***	-0.0955**	1.0000	
CCI	-0.1490***	0.0199	-0.1114***	0.2179***	0.1998***	-0.0103	-0.1024**	0.2998***	0.2385***	-0.0382	0.1517***	1.0000

[15] http://www.bls.gov/.

Table 3: Parameter Estimates of Ordinary Linear Regressions

This table reports estimation results for the unconditional OLS model

$$MOM_t = \alpha + \beta_1 DIV_{t-1} + \beta_2 TB_{t-1} + \beta_3 TERM_{t-1} + \beta_4 CRD_{t-1} + \beta_5 IDPgrowth_{t-1} + \beta_6 INF_{t-1} + \beta_7 MKT_t + \beta_8 SMB_t + \beta_9 HML_t + \beta_{10} Liquidity_t + \beta_{11} CCI_t + \varepsilon_t$$

where MOM_t denotes momentum return in month t; DIV_{t-1} is the dividend yield in month $t-1$; TB_{t-1} is the yield on three-month T-bills in month $t-1$; $TERM_{t-1}$ is the term spread in month $t-1$; CRD_{t-1} is the credit spread in month $t-1$; $IDPgrowth_{t-1}$ is the growth rate of industrial production in month $t-1$; INF_{t-1} is the inflation rate in month $t-1$; MKT_t, SMB_t and HML_t are the market factor, the size factor and the value factor in the Fama-French three-factor model in month t, respectively; $Liquidity_t$ is the Pastor-Stambaugh (2003) liquidity factor in month t; CCI_t is the change in the Consumer Confidence Index in month t. α is the intercept, β_i is the coefficient of the ith independent variable, ε_t is the residual of regression in month t, and I is the number of independent variables. DIV is the dividend yield, i.e., total dividend payments accruing to the Center for Research in Security Prices (CRSP) value-weighted index over the previous 12 months divided by the current level of the index (Pontiff and Schall (1998)). TB denotes the three-month T-bills rate. TERM is term spread, i.e., the difference between the market yield on Treasury bonds with 10 years to maturity and the yield on the three-month T-bills (TB). CRD (credit) stands for the difference between yield on bonds with a Moody's rating of BAA and the yield on bonds rated AAA by Moody's. IDP growth rate is continuously compounded, seasonally adjusted and measured as the log difference of the industrial production (IDP). CCI is the change in the Consumer Confidence Index by taking the first log difference of the Consumer Confidence Index from OECD Data. We use data from August 1962 to December 2014 (629 months). We report t-statistics in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 3 Continued

constant	DIV	TB	TERM	CRD	IDP growth	INF	MKT	SMB	HML	Liquidity	CCI	Adjusted **R^2**
0.8236 (1.60)		0.1920** (2.41)	0.3470** (2.09)	-1.7385*** (-4.16)		0.4967 (0.56)						0.0250
0.7317 (1.37)		0.1855** (2.31)	0.3246* (1.91)	-1.6222*** (-3.59)	0.1658 (0.68)	0.5016 (0.56)						0.0241
0.5808 (1.01)	-0.5058** (-2.02)	0.1894** (2.08)	0.1507 (0.93)		0.4426* (1.94)	0.9027 (0.95)						0.0103
1.1265** (1.99)	-0.3259 (-1.28)	0.2489*** (2.73)	0.3985** (2.33)	-1.6015*** (-3.72)		0.9152 (0.97)						0.0260
1.0349* (1.77)	-0.3222 (-1.26)	0.2420*** (2.63)	0.3765** (2.16)	-1.4914*** (-3.22)	0.1590 (0.65)	0.9151 (0.97)						0.0251
0.7686 (1.31)	-0.2813 (-1.11)	0.2219** (2.42)	0.4109** (2.37)	-1.2533*** (-2.69)	0.1962 (0.81)	0.7341 (0.78)					-2.4638*** (-3.03)	0.0377
1.0722 (1.85)	-0.1719 (-0.67)	0.2025** (2.21)	0.3359 (1.95)	-1.3388*** (-2.93)	0.1696 (0.71)	0.8017 (0.85)	-0.1294*** (-3.18)	-0.1888*** (-3.35)	-0.2020*** (-3.32)	0.0527 (1.88)		0.0655
0.9412 (0.61)	-0.1729 (-0.67)	0.1953** (2.13)	0.3581** (2.08)	-1.2035*** (-2.60)	0.1836 (0.77)	0.7596 (0.81)	-0.1124*** (-2.69)	-0.1731*** (-3.04)	-0.1919*** (-3.14)	0.0555** (1.98)	-1.4988* (-1.77)	0.0687

Table 4: Coefficient Estimates of Two-state Univariate Markov Regime Switching Regressions

This table presents coefficient estimates for the two-state univariate Markov regime switching regression

$$MOM_t = \alpha_{S_t} + \beta_{1,S_t} DIV_{t-1} + \beta_{2,S_t} TB_{t-1} + \beta_{3,S_t} TERM_{t-1} + \beta_{4,S_t} CRD_{t-1} + \beta_{5,S_t} IDPgrowth_{t-1} + \beta_{6,S_t} INF_{t-1} + \beta_{7,S_t} MKT_t + \beta_{8,S_t} SMB_t + \beta_{9,S_t} HML_t + \beta_{10,S_t} Liquidity_t + \beta_{11,S_t} CCI_t + \varepsilon_{t,S_t}$$

where MOM_t is the momentum return in month t; DIV_{t-1} is the dividend yield in month $t-1$; TB_{t-1} is the yield on three-month T-bills in month $t-1$; $TERM_{t-1}$ is the term spread in month $t-1$; CRD_{t-1} is the credit spread in month $t-1$; $IDPgrowth_{t-1}$ is the growth rate of industrial production in month $t-1$; INF_{t-1} is the inflation rate in month $t-1$; MKT_t, SMB_t and HML_t are the market factor, the size factor and the value factor in the Fama-French three-factor model in month t, respectively; $Liquidity_t$ is the Pastor-Stambaugh (2003) liquidity factor in month t; CCI_t is the change in the Consumer Confidence Index in month t. α_{S_t} and β_{i,S_t} denote intercept in state S_t and coefficients of independent variables in state S_t, respectively; ε_{t,S_t} is the residual of regression in month t in state S_t. DIV is the dividend yield, i.e., total dividend payments accruing to the Center for Research in Security Prices (CRSP) value-weighted index over the previous 12 months divided by the current level of the index (Pontiff and Schall (1998)). TB denotes the three-month T-bills rate. TERM is term spread, i.e., the difference between the market yield on Treasury bonds with 10 years to maturity and the yield on the three-month T-bills (TB). CRD (credit) stands for the difference between yield on bonds with a Moody's rating of BAA and the yield on bonds rated AAA by Moody's. IDP growth rate is continuously compounded, seasonally adjusted and measured as the log difference of the industrial production (IDP). INF (inflation) stands for the inflation rate, i.e., the log difference of the consumer price index for all urban consumers, all items less food and energy. The CPI is seasonally adjusted and obtained from the Bureau of Labor Statistics website. MKT is the difference between the market return and the risk-free rate. MKT, SMB and HML are the market factor, the size factor and the value factor in the Fama-French three-factor model (Fama and French (1993)), respectively. Liquidity is the Pastor-Stambaugh (2003) liquidity factor. CCI is the change in the Consumer Confidence Index by taking the first log difference of the Consumer Confidence Index from OECD Data. We identify state 1 as an expansion state and state 2 as a contraction state. We use data from August 1962 to December 2014 (629 months). We report *t*-statistics in parentheses. We use Wald tests for the equality of the parameters across the two regimes. Test statistics is given by the formula $\frac{\left|\hat{\beta}_{i,S_1} - \hat{\beta}_{i,S_2}\right|}{\sqrt{Var(\hat{\beta}_{i,S_1} - \hat{\beta}_{i,S_2})}}$. We report p-values in brackets. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. We report adjusted McFadden's Pseudo R^2 in the last column.

Table 4 Continued

		constant	DIV	TB	TERM	CRD	IDP growth	INF	MKT	SMB	HML	Liquidity	CCI	Pseudo R^2
(1)	State 1	0.4612 (1.23)		0.1277*** (2.01)	0.2053 (1.58)	-0.6778* (-1.85)		0.5511 (0.92)						
	State 2	0.5208 (0.24)		0.3801 (1.17)	-0.2594 (-0.45)	-0.4477 (-0.34)		-5.3293 (-1.41)						-0.0014
Test Statistics		0.0264 [0.97]		0.7353 [0.46]	0.7789 [0.43]	0.1651 [0.86]		1.5386 [0.12]						
(2)	State 1	0.4023 (1.05)		0.1143* (1.85)	0.1524 (1.15)	-0.4863 (-1.28)	0.1322 (0.73)	0.4734 (0.78)						
	State 2	1.3076 (0.68)		0.3045 (1.02)	-0.2038 (-0.34)	-1.0988 (-0.85)	-0.3936 (-0.54)	-4.2993 (-1.26)						-0.0015
Test Statistics		0.4524 [0.65]		0.6059 [0.54]	0.5746 [0.56]	0.4473 [0.65]	0.6986 [0.48]	1.3757 [0.16]						
(3)	State 1	0.0219 (0.00)	0.2208 (0.00)	0.0597 (0.83)	0.0263 (0.00)		0.1185 (1.11)	-0.3739 (-0.58)						
	State 2	2.7500** (1.87)	-1.7895*** (-2.63)	0.1440 (0.56)	-0.0196 (-0.08)		0.6993 (1.09)	4.2487 (1.21)						0.0018
Test Statistics		3.6431*** [0.00]	3.0423*** [0.00]	0.3105 [0.75]	0.2233 [0.82]		0.9021 [0.36]	1.2599 [0.20]						
(4)	State 1	0.6200* (1.65)	0.0936 (0.48)	0.1315* (1.85)	0.1415 (1.10)	-0.7451** (-2.07)		-0.4134 (-0.64)						
	State 2	0.4532 (0.13)	1.0107 (0.95)	-0.2708 (-0.45)	-1.1489 (-1.13)	-0.0425 (-0.02)		-1.6809 (-0.27)						-0.0042
Test Statistics		0.0491 [0.96]	0.8388 [0.40]	0.6625 [0.50]	1.2577 [0.20]	0.3971 [0.69]		0.2062 [0.83]						

Table 4 Continued

		constant	DIV	TB	TERM	CRD	IDP growth	INF	MKT	SMB	HML	Liquidity	CCI	Pseudo R^2
(5)	State 1	0.8465*** (2.18)	0.0224 (0.11)	0.1297* (1.81)	0.1923 (1.48)	-0.9074** (-2.43)	-0.2275 (-1.30)	-0.1327 (-0.20)						
	State 2	3.3799 (0.86)	0.5639 (0.49)	-0.3917 (-0.54)	-1.4380 (-1.21)	-0.7128 (-0.38)	0.1155 (0.12)	-1.0414 (-0.15)						-0.0040
Test Statistics		0.6446 [0.51]	0.4605 [0.64]	0.7117 [0.47]	1.3541 [0.17]	0.1009 [0.91]	0.3450 [0.73]	0.1335 [0.89]						
(6)	State 1	0.4875 (1.05)	-0.0696 (-0.25)	0.0923 (1.29)	0.0674 (0.51)	-0.0053 (-0.01)	0.3616** (2.02)	0.3034 (0.42)					-2.1896*** (-3.37)	
	State 2	-0.4960 (-0.16)	0.3000 (0.15)	0.3451 (0.65)	-0.1106 (-0.11)	-1.4029 (-0.56)	-1.1686 (-1.38)	-2.5932 (-0.48)					-3.8642 (-1.36)	-0.0013
Test Statistics		0.3098 [0.75]	0.1729 [0.86]	0.4614 [0.64]	0.1750 [0.86]	0.4971 [0.61]	1.7553* [0.07]	0.5402 [0.58]					0.5528 [0.58]	
(7)	State 1	0.7512** (1.98)	-0.0490 (-0.27)	0.2131*** (3.32)	0.3011*** (2.53)	-1.2226*** (-3.30)	-0.0082 (-0.04)	-0.3908 (-0.62)	0.0993*** (3.64)	0.1697*** (4.63)	-0.1568*** (-4.11)	0.0381* (2.03)		
	State 2	-3.6634 (-1.20)	0.3573 (0.28)	0.3548 (0.64)	-0.2336 (-0.24)	1.1735 (0.72)	-1.5252 (-1.70)	-2.8956 (-0.49)	-0.2661*** (-2.49)	-0.4978*** (-3.45)	-0.0979 (-0.67)	-0.1388 (-1.49)		0.0019
Test Statistics		1.4206 [0.15]	0.3219 [0.74]	0.2548 [0.79]	0.5570 [0.57]	1.4577 [0.14]	1.6370 [0.10]	0.4213 [0.67]	3.2879*** [0.00]	3.2524*** [0.00]	0.3951 [0.69]	1.8251* [0.06]		
(8)	State 1	-0.3392 (-0.72)	0.1399 (0.70)	0.2167*** (2.94)	0.3659*** (2.94)	-1.1470*** (-2.77)	0.8940*** (4.27)	-0.9760 (-1.30)	0.2036*** (5.57)	0.1542*** (2.87)	-0.0867 (-1.35)	-0.0027 (-0.06)	-2.7958*** (-4.10)	
	State 2	-0.5606 (-0.36)	1.1873* (1.63)	0.3351 (1.51)	0.1333 (0.21)	-2.4662** (-1.99)	-0.4223 (-0.70)	-4.5108* (-1.64)	-0.3259*** (-3.59)	-0.2206* (-1.78)	-0.1388 (-0.97)	-0.0515 (-0.85)	1.3340 (0.63)	0.0078
Test Statistics		2.6701*** [0.00]	0.5348 [0.59]	0.5977 [0.55]	0.8590 [0.39]	1.7509* [0.08]	2.2949** [0.02]	0.8702 [0.38]	3.7023*** [0.00]	3.6169*** [0.00]	0.3519 [0.72]	2.4868** [0.01]	0.0798 [0.93]	

Table 5: Parameter Estimates of Two-state Multivariate Markov Regime Switching Regression

This table presents coefficient estimates for the two-state multivariate Markov regime switching regression

$$\boldsymbol{Y_t} = \begin{bmatrix} MOM_t \\ IDPgrowth_t \end{bmatrix} = \boldsymbol{X\beta} + \begin{bmatrix} \boldsymbol{\varepsilon}_{1t,S_t} \\ \boldsymbol{\varepsilon}_{2t,S_t} \end{bmatrix}$$

where MOM_t is the momentum return in month t; $IDPgrowth_t$ is the growth rate of industrial production in month t; $\boldsymbol{X}$ is the vector of lagged independent variables including DIV_{t-1}, TB_{t-1}, $TERM_{t-1}$, CRD_{t-1}, INF_{t-1}, risk factors MKT_t, SMB_t, HML_t, $Liquidity_t$, and proxy for investor sentiment CCI_t; $\boldsymbol{\beta}$ is the vector of estimated coefficients; and $(\boldsymbol{\varepsilon}'_{1t,S_t}\boldsymbol{\varepsilon}'_{2t,S_t})' \sim \left(0, \boldsymbol{\Sigma}_{S_t}\right)$ denotes the residual of regression in month t in state S_t. DIV is the dividend yield, i.e., total dividend payments accruing to the Center for Research in Security Prices (CRSP) value-weighted index over the previous 12 months divided by the current level of the index (Pontiff and Schall (1998)). TB denotes the three-month T-bills rate. TERM is term spread, i.e., the difference between the market yield on Treasury bonds with 10 years to maturity and the yield on the three-month T-bills (TB). CRD (credit) stands for the difference between yield on bonds with a Moody's rating of BAA and the yield on bonds rated AAA by Moody's. IDP growth rate is continuously compounded, seasonally adjusted and measured as the log difference of the industrial production (IDP). INF (inflation) stands for the inflation rate, i.e., the log difference of the consumer price index for all urban consumers, all items less food and energy. The CPI is seasonally adjusted and obtained from the Bureau of Labor Statistics website. MKT is the difference between the market return and the risk-free rate. MKT, SMB and HML are the market factor, the size factor and the value factor in the Fama-French three-factor model (Fama and French (1993)), respectively. Liquidity is the Pastor-Stambaugh (2003) liquidity factor. CCI is the change in the Consumer Confidence Index by taking the first log difference of the Consumer Confidence Index from OECD Data. We identify state 1 as an expansion state and state 2 as a contraction state. We use data from August 1962 to December 2014 (629 months). σ^2 is the percentage of variance of residuals of the regression. We report *t*-statistics in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. We report adjusted McFadden's Pseudo R^2.

Table 5 Continued

Variable	(1)				(2)				(3)			
	State 1		State 2		State 1		State 2		State 1		State 2	
	MOM	IDP growth	MOM	IDP growth	MOM	IDP growth	MOM	IDP growth	MOM	IDP growth	MOM	IDP growth
constant	0.9404**	0.2781***	-0.2847	0.3368	0.8640**	0.4940***	-0.0249	0.7761***	0.8137**	0.4844***	1.7976	0.8005**
	(2.13)	(2.90)	(-0.10)	(1.03)	(2.06)	(5.68)	(-0.00)	(2.48)	(1.92)	(5.41)	(1.00)	(2.14)
DIV	0.0053	0.0179	-0.0154	-0.2771**	0.0167	0.0818*	0.3928	-0.0211	0.1380	0.0011	-0.0470	-0.0654
	(0.02)	(0.43)	(-0.01)	(-2.05)	(0.08)	(1.89)	(0.35)	(-0.16)	(0.79)	(0.02)	(-0.03)	(-0.49)
TB	0.0179	-0.0052	0.1812	0.0577	0.0230	-0.0045	0.2178	-0.0310				
	(0.25)	(-0.34)	(0.37)	(1.24)	(0.36)	(-0.32)	(0.48)	(-0.79)				
TERM	-0.0459	0.0396*	-0.6311	-0.1437					0.0436	0.0814***	-0.3465	-0.1215
	(-0.40)	(1.58)	(-0.57)	(-1.32)					(0.36)	(3.14)	(-0.39)	(-1.06)
CRD					-0.3006	-0.2842***	-1.3147	-0.7344***	-0.4319	-0.3632***	-1.7828	-0.5680***
					(-0.82)	(-4.10)	(-0.73)	(-4.05)	(-1.07)	(-4.82)	(-1.01)	(-2.58)
INF	-0.4633	0.0012	0.2526	0.0390	0.4877	-0.2630**	-2.0151	0.4464	-0.0906	0.2460*	3.0286	-0.0284
	(-0.59)	(0.00)	(0.04)	(0.07)	(0.69)	(-1.93)	(-0.34)	(0.99)	(-0.11)	(1.87)	(0.59)	(-0.05)
MKT												
SMB												
HML												
Liquidity												
CCI												
σ^2	6.9532***	0.2943***	55.9905***	0.9601***	6.1411***	52.7473***	0.2906***	0.9470***	6.7349***	0.3023***	56.5136***	0.9837***
	(16.24)	(15.90)	(7.59)	(9.76)	(14.97)	(7.64)	(14.82)	(11.30)	(15.62)	(16.34)	(6.68)	(11.55)
Pseudo R^2	0.0035				0.0053				0.0077			

Table 5 Continued

Variable	(4)				(5)				(6)			
	State 1		State 2		State 1		State 2		State 1		State 2	
	MOM	IDP growth	MOM	IDP growth	MOM	IDP growth	MOM	IDP growth	MOM	IDP growth	MOM	IDP growth
constant	0.8456**	0.5386***	3.2430	0.6538	1.0512**	0.5207***	-3.7176	0.5817	0.9236**	0.6479***	1.3023	0.1779
	(2.22)	(6.91)	(0.96)	(1.52)	(2.42)	(5.93)	(-0.83)	(1.18)	(2.20)	(7.10)	(0.38)	(0.47)
DIV					-0.1212	0.0074	0.3767	0.1165	-0.1388	-0.0379	0.8239	0.0407
					(-0.67)	(0.19)	(0.24)	(0.64)	(-0.71)	(-0.91)	(0.64)	(0.25)
TB	0.1298**	0.0117	-0.1628	-0.0054	0.0960	0.0032	0.3573	-0.0301	0.1006	0.0027	0.0638	0.0778
	(1.98)	(0.76)	(-0.30)	(-0.10)	(1.31)	(0.19)	(0.48)	(-0.47)	(1.31)	(0.15)	(0.10)	(1.58)
TERM	0.1414	0.0769***	-1.0729	-0.0500	0.1473	0.0757***	-0.0600	-0.1444	0.1614	0.0589*	-0.3483	0.2113*
	(1.09)	(2.54)	(-0.89)	(-0.38)	(1.13)	(2.45	(-0.03)	(-0.93)	(1.17)	(1.82)	(-0.34)	(1.80)
CRD	-0.8150**	-0.3631***	-0.1725	-0.6599***	-0.5444	-0.3571***	-0.0565	-0.6741***	-0.5154	-0.3380***	-2.5067	-0.8869***
	(-1.96)	(-4.36)	(-0.08)	(-3.17)	(-1.27)	(-4.29)	(-0.02)	(-2.46)	(-1.23)	(-3.89)	(-1.26)	(-4.01)
INF	-0.1584	-0.1153	-3.8402	-0.0064					0.5280	0.0055	-1.8133	0.0003
	(-0.23)	(-0.91)	(-0.65)	(-0.01)					(0.69)	(0.03)	(-0.29)	(0.00)
MKT												
SMB												
HML												
Liquidity												
CCI												
σ^2	6.9982***	0.3077***	70.9644***	1.0412***	7.1100***	0.3066***	69.1816***	1.1707***	6.0540***	0.2749***	57.9292***	1.0191***
	(16.89)	(16.54)	(5.50)	(8.74)	(16.69)	(16.39)	(5.58)	(7.28)	(14.06)	(14.02)	(7.12)	(8.67)
Pseudo R^2	0.0046				0.0052				0.0075			

Table 5 Continued

Variable	(7)				(8)				(9)			
	State 1		State 2		State 1		State 2		State 1		State 2	
	MOM	IDP growth	MOM	IDP growth	MOM	IDP growth	MOM	IDP growth	MOM	IDP growth	MOM	IDP growth
constant	0.7255* (1.77)	0.5929*** (6.39)	-0.5406 (-0.13)	-0.0669 (-0.16)	0.9938** (2.32)	0.7021*** (5.36)	-0.2074 (-0.03)	-0.2063 (-0.67)	0.9559** (2.14)	0.7950*** (6.03)	3.4987 (0.43)	-0.6976** (-2.81)
DIV	-0.2330 (-1.27)	0.0044 (0.10)	0.0832 (0.05)	0.1034 (0.60)	-0.1389 (-0.69)	-0.0634 (-1.09)	1.6704 (0.77)	-0.0136 (-0.11)	-0.0535 (-0.25)	-0.0924* (-1.67)	0.5299 (0.18)	-0.0404 (-0.36)
TB	0.1275* (1.78)	-0.0048 (-0.27)	-0.0246 (-0.03)	0.0509 (0.92)	0.1943*** (2.87)	0.0530*** (2.80)	0.0132 (0.01)	0.0686 (1.29)	0.1581** (2.30)	0.0366* (1.96)	-0.0672 (-0.04)	0.1777*** (3.90)
TERM	0.2540* (1.91)	0.0595* (1.82)	-0.7978 (-0.59)	0.1703 (1.29)	0.2321* (1.75)	0.1598*** (4.18)	-0.2914 (-0.17)	0.0081 (0.09)	0.1816 (1.43)	0.1381*** (3.81)	-1.2659 (-0.52)	0.2029*** (2.86)
CRD	-0.2349 (-0.58)	-0.4017*** (-4.43)	0.5170 (0.20)	-0.7155*** (-3.18)	-0.8305*** (-2.64)	-0.7015*** (-8.93)	-2.6593 (-0.92)	-0.1306 (-0.55)	-0.5511* (-1.71)	-0.6895*** (-9.01)	-2.6665 (-0.69)	-0.1456 (-0.66)
INF	0.3495 (0.46)	0.1010 (0.71)	0.5345 (0.08)	0.0095 (0.01)	-0.0954 (-0.13)	-0.0837 (-0.47)	-3.0499 (-0.28)	-0.1027 (-0.18)	-0.9516 (-1.26)	0.1389 (0.80)	-2.0285 (-0.13)	-0.2968 (-0.61)
MKT					-0.0661*** (-2.50)	0.0156 (2.01)	-0.3751* (-1.80)	-0.0081 (-0.37)	-0.0863*** (-3.09)	0.0120 (1.57)	-0.2222 (-0.65)	-0.0086 (-0.44)
SMB					0.0935** (2.35)	-0.0154 (-1.33)	-0.5166** (-2.21)	0.0063 (0.28)	0.0677 (1.53)	-0.0139 (-1.21)	-0.3362 (-1.22)	0.0002 (0.00)
HML					-0.3448*** (-9.35)	0.0076 (0.62)	0.0804 (0.26)	-0.0006 (-0.02)	-0.2295*** (-5.61)	0.0050 (0.41)	-0.0140 (-0.03)	-0.0111 (-0.55)
Liquidity					0.0467*** (2.57)	0.0150*** (2.66)	-0.0658 (-0.40)	-0.0095 (-0.79)	0.0431** (2.18)	0.0132** (2.43)	-0.0746 (-0.39)	-0.0044 (-0.45)
CCI	-2.4223*** (-4.06)	0.4352*** (2.93)	-3.5451 (-0.89)	-1.0285* (-1.85)					-2.1830*** (-3.47)	-0.0128 (-0.07)	3.9951 (0.52)	0.1330 (0.30)
σ^2	6.0614*** (14.64)	0.2841*** (14.79)	68.4809*** (5.80)	1.0607*** (8.41)	7.0150*** (15.00)	0.4860*** (19.05)	52.48*** (4.34)	0.2334*** (3.85)	7.1632*** (15.36)	0.4722*** (19.67)	78.2126*** (3.20)	0.2013*** (3.96)
Pseudo R^2	0.0099				0.0016				0.0032			

Table 6: Covariance Matrix of Errors from Two-state Multivariate Markov Regime Switching Regression

This table presents covariance matrix of errors from the two-state multivariate Markov regime switching regression

$$\boldsymbol{Y_t} = \begin{bmatrix} MOM_t \\ IDPgrowth_t \end{bmatrix} = \boldsymbol{X\beta} + \begin{bmatrix} \boldsymbol{\varepsilon}_{1t,S_t} \\ \boldsymbol{\varepsilon}_{2t,S_t} \end{bmatrix}$$

where MOM_t is the momentum return in month t; $IDPgrowth_t$ is the growth rate of industrial production in month t; $\boldsymbol{X}$ is the vector of lagged independent variables including DIV_{t-1}, TB_{t-1}, $TERM_{t-1}$, CRD_{t-1}, INF_{t-1}, risk factors MKT_t, SMB_t, HML_t, $Liquidity_t$, and proxy for investor sentiment CCI_t; $\boldsymbol{\beta}$ is the vector of estimated coefficients; and $(\boldsymbol{\varepsilon}'_{1t,S_t}\boldsymbol{\varepsilon}'_{2t,S_t})' \sim (0, \boldsymbol{\Sigma}_{S_t})$ denotes the residual of regression in month t in state S_t. We identify state 1 as an expansion state and state 2 as a contraction state. The data covers the period August 1962 to December 2014.

	Covariance matrix	
State 1	7.1632	0.0220
	0.0220	0.4722
State 2	78.2126	0.3474
	0.3474	0.2013

Table 7: Summary Statistics for Monthly Pure Momentum

This table presents summary statistics for the monthly pure momentum returns for the period August 1962 to December 2014. The sample includes data of 629 months. The pure momentum $PM_t$is measured as the unexplained portion (residual) of the following two-state univariate Markov regime switching regression: $MOM_t = \alpha_{S_t} + \beta_{1,S_t}DIV_{t-1} + \beta_{2,S_t}TB_{t-1} + \beta_{3,S_t}TERM_{t-1} + \beta_{4,S_t}CRD_{t-1} + \beta_{5,S_t}IDPgrowth_{t-1} + \beta_{6,S_t}INF_{t-1} + \beta_{7,S_t}MKT_t + \beta_{8,S_t}SMB_t + \beta_{9,S_t}HML_t + \beta_{10,S_t}Liquidity_t + \beta_{11,S_t}CCI_t + \varepsilon_{t,S_t}$.

Pure momentum	Mean (%)	Standard deviation (‰)	Min (%)	Max (%)	Median (%)	5% percentile	10% percentile	90% percentile	95% percentile
Full sample	0.0361	0.3870	-26.9278	18.1440	0.1378	-5.8546	-3.8021	3.6703	6.6982
State 1	-0.0419	1.9587	-5.9212	5.3091	0.0367	-3.6413	-2.6833	2.3322	3.0119
State 2	0.1978	6.1742	-26.9278	18.1440	0.5527	-8.4738	-7.0885	7.7511	9.2769

Table 8: Correlations between Pure Momentum and Market Returns

This table presents correlation coefficients between the pure momentum and value-weighted return on CRSP stock market portfolio, equal-weighted return on CRSP stock market portfolio and return on S&P 500 Index during the period August 1962 to December 2014. The pure momentum $PM_t$is measured as the unexplained portion (residual) of the following two-state univariate Markov regime switching regression: $MOM_t = \alpha_{S_t} + \beta_{1,S_t}DIV_{t-1} + \beta_{2,S_t}TB_{t-1} + \beta_{3,S_t}TERM_{t-1} + \beta_{4,S_t}CRD_{t-1} + \beta_{5,S_t}IDPgrowth_{t-1} + \beta_{6,S_t}INF_{t-1} + \beta_{7,S_t}MKT_t + \beta_{8,S_t}SMB_t + \beta_{9,S_t}HML_t + \beta_{10,S_t}Liquidity_t + \beta_{11,S_t}CCI_t + \varepsilon_{t,S_t}$. Data of S&P 500 Index and CRSP Stock Market Index are obtained from CRSP. S&P 500 Index monthly returns are calculated by (SPINDX(t)/SPINDX(t-1)) – 1, where SPINDX is the level of the Standard & Poor's 500 Composite Index at the end of the trading day or month. For CRSP Stock Market Indexes, the market groups of securities are the individual NYSE, AMEX, and NASDAQ markets, as well as the NYSE/AMEX and NYSE/AMEX/NASDAQ market combinations. We also include Published S&P 500 and NASDAQ Composite Index Data. The 25 monthly portfolios are constructed by double-sorting stocks on size (market equity) and book-to-market equity ratio, which include NYSE, AMEX, and NASDAQ stocks with prior market equity and book equity data. We obtain 25 portfolios monthly returns from Kenneth R. French Data Library. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Correlations between pure momentum and return on CRSP Stock Market Indexes and S&P 500 Index

	CRSP Stock Market Index (value-weighted)	CRSP Stock Market Index (equal-weighted)	S&P 500 Index monthly returns
Pure momentum	-0.0646	-0.1364***	-0.0883**

Panel B: Correlations between pure momentum and 25 portfolios monthly returns (value-weighted)

	Mean	Min	Max	Median
Pure momentum	-0.0831	-0.1615	-0.0051	-0.0845

Panel C: Correlations between pure momentum and 25 portfolios monthly returns (equal-weighted)

	Mean	Min	Max	Median
Pure momentum	-0.1613	-0.2375	-0.1126	-0.1584

Table 9: Time-series Regression for Excess Returns on Portfolios

This table reports estimation results for the time-series regression

$$R_{it} - R_{ft} = \alpha_i + b_i\left(R_{Mt} - R_{ft}\right) + s_i SMB_t + h_i HML_t + l_i Liquidity_t + p_i PM_t + v_{it} \qquad (7)$$

where R_{it} is the return for portfolio i in month t; R_{ft} is the risk-free rate in month t; R_{Mt} is the market return in month t; SMB_t, HML_t are the size factor and the value factor in the Fama-French three-factor model (Fama and French (1993)) in month t, respectively; $Liquidity_t$ is the Pastor-Stambaugh (2003) liquidity factor in month t; PM_t is the pure momentum we obtained in in month t; α_i is the intercept; b_i, s_i, h_i, l_i, and p_i are the factor loadings; v_{it} is the residual of the regression. We use data from August 1962 to December 2014 (629 months). The monthly portfolios are constructed by double-sorting stocks on size (market equity) and book-to-market equity ratio. We obtain monthly portfolio returns, market returns, risk free rate, SMB, HML from Kenneth R. French Data Library. The pure momentum $PM_t$is measured as the unexplained portion (residual) of the following two-state univariate Markov regime switching regression: $MOM_t = \alpha_{S_t} + \beta_{1,S_t} DIV_{t-1} + \beta_{2,S_t} TB_{t-1} + \beta_{3,S_t} TERM_{t-1} + \beta_{4,S_t} CRD_{t-1} + \beta_{5,S_t} IDPgrowth_{t-1} + \beta_{6,S_t} INF_{t-1} + \beta_{7,S_t} MKT_t + \beta_{8,S_t} SMB_t + \beta_{9,S_t} HML_t + \beta_{10,S_t} Liquidity_t + \beta_{11,S_t} CCI_t + \varepsilon_{t,S_t}$. t(·) denotes *t*-statistics. S(e) denotes standard error of residuals. We report adjusted R^2.

Table 9 Continued

	Book-to-market equity ratio Quintiles									
Size	low	2	3	4	high	low	2	3	4	high
	$R_{it} - R_{ft} = \alpha_i + b_i(R_{Mt} - R_{ft}) + s_i SMB_t + h_i HML_t + l_i Liquidity_t + p_i PM_t + v_{it}$									
			α					t(α)		
Small	-0.5965	-0.1071	-0.0631	0.1052	0.1864	-3.38	-0.75	-0.61	1.16	2.31
2	-0.2366	-0.0278	0.1187	0.0899	-0.0998	-1.92	-0.31	1.71	1.35	-1.42
3	-0.1273	0.0996	0.0748	0.1051	0.1550	-1.17	1.28	1.01	1.47	1.90
4	0.0931	-0.0383	0.0268	0.1098	0.0366	1.00	-0.48	0.33	1.46	0.39
Big	0.1570	0.1224	0.0257	-0.1249	-0.1573	2.98	1.72	0.30	-1.48	-1.37
			b					t(b)		
Small	1.2471	1.1115	1.0202	0.9647	1.0159	32.96	36.26	45.92	49.63	58.63
2	1.2205	1.0660	0.9899	0.9952	1.1164	46.31	55.75	66.46	69.85	74.15
3	1.1861	1.0534	0.9836	0.9674	1.0428	51.06	62.99	62.03	63.31	59.67
4	1.1391	1.0645	1.0425	1.0003	1.0862	57.42	63.02	60.15	61.98	54.22
Big	0.9694	0.9462	0.9176	0.9214	0.9904	85.78	62.01	49.96	50.83	40.18

Table 9 Continued

	Book-to-market equity ratio Quintiles									
Size	low	2	3	4	high	low	2	3	4	high
	$R_{it} - R_{ft} = \alpha_i + b_i(R_{Mt} - R_{ft}) + s_i SMB_t + h_i HML_t + l_i Liquidity_t + p_i PM_t + v_{it}$									
			s					t(s)		
Small	1.0007	0.9610	0.8685	0.8590	0.9884	19.14	22.69	28.29	31.98	41.28
2	0.7694	0.7456	0.7343	0.4901	0.8087	21.13	28.22	35.67	34.04	38.87
3	0.5373	0.5086	0.4511	0.4637	0.5816	16.74	22.01	20.59	21.96	24.08
4	0.1991	0.2340	0.2348	0.2385	0.3530	7.26	10.02	9.80	10.69	12.75
Big	-0.2306	-0.1181	-0.1099	-0.0490	0.0636	-14.77	-5.60	-4.33	-1.95	1.86
			h					t(h)		
Small	-0.0424	0.2903	0.4459	0.5908	0.7580	-0.74	6.31	13.38	20.26	29.16
2	-0.2373	0.2152	0.4208	0.6074	0.8488	-6.00	7.50	18.83	28.29	37.58
3	-0.2985	0.1852	0.4288	0.5706	0.7444	-8.56	7.78	18.02	24.89	28.39
4	-0.2959	0.1932	0.3910	0.5565	0.7193	-9.94	7.62	15.04	22.98	23.93
Big	-0.3718	0.0198	0.2035	0.4857	0.6485	-21.93	0.86	7.38	17.86	17.54

Table 9 Continued

	Book-to-market equity ratio Quintiles									
Size	low	2	3	4	high	low	2	3	4	high
	$R_{it} - R_{ft} = \alpha_i + b_i(R_{Mt} - R_{ft}) + s_i SMB_t + h_i HML_t + l_i Liquidity_t + p_i PM_t + v_{it}$									
	l					t(l)				
Small	-0.0437	-0.0281	-0.0180	-0.0094	0.0094	-1.70	-1.35	-1.19	-0.71	0.80
2	-0.0333	-0.0063	-0.0013	0.0021	-0.0179	-1.86	-0.48	-0.13	0.22	-1.75
3	-0.0269	0.0053	0.0121	0.0123	0.0082	-1.70	0.46	1.12	1.19	0.69
4	-0.0109	0.0122	0.0171	0.0168	0.0269	-0.81	1.07	1.45	1.53	1.98
Big	-0.0054	0.0242	0.0262	-0.0029	-0.0032	-0.74	2.33	2.10	-0.23	-0.19
	p					t(p)				
Small	0.1428	0.1488	0.1068	0.0922	0.0387	3.58	4.60	4.56	4.50	2.12
2	0.0905	0.0297	0.0479	0.0328	0.0204	3.26	1.47	3.05	2.19	1.29
3	0.0769	0.0040	-0.0100	-0.0141	-0.0415	3.14	0.23	-0.60	-0.88	-2.25
4	0.0828	-0.0263	-0.0782	-0.0473	-0.1014	3.96	-1.48	-4.28	-2.78	-4.80
Big	-0.0221	-0.0232	-0.0454	-0.1016	-0.1054	-1.85	-1.44	-2.35	-5.32	-4.06

Table 9 Continued

	Book-to-market equity ratio Quintiles									
Size	low	2	3	4	high	low	2	3	4	high
	$R_{it} - R_{ft} = \alpha_i + b_i(R_{Mt} - R_{ft}) + s_i SMB_t + h_i HML_t + l_i Liquidity_t + p_i PM_t + v_{it}$									
	R^2					s(e)				
Small	0.77	0.79	0.86	0.88	0.91	3.81	3.08	2.23	1.95	1.74
2	0.86	0.89	0.92	0.92	0.93	2.65	1.92	1.50	1.43	1.51
3	0.87	0.90	0.89	0.90	0.89	2.33	1.68	1.59	1.53	1.76
4	0.88	0.89	0.88	0.88	0.86	1.99	1.70	1.74	1.62	2.01
Big	0.94	0.87	0.81	0.82	0.75	1.13	1.53	1.85	1.82	2.48

Table 10: Cross-sectional Regression for Excess Returns on Portfolios

This table reports estimation results for the cross-sectional regression

$$E[R_i - R_f] = \beta_i \lambda + w_i \qquad (6)$$

where R_i is the return for portfolio i; R_f is the risk-free rate; $E[R_i - R_f]$ is the estimate of the mean excess return for portfolio i; β_i is the estimates of factor loadings from the time-series regression $R_{it} - R_{ft} = \alpha_i + b_i(R_{Mt} - R_{ft}) + s_i SMB_t + h_i HML_t + l_i Liquidity_t + p_i PM_t + v_{it}$; λ is the risk premium; w_i is the residual of the regression. We use data from August 1962 to December 2014 (629 months). The monthly portfolios are constructed by double-sorting stocks on size (market equity) and book-to-market equity ratio. We use Shanken (1992) correction estimating the risk premium. We report *t*-statistics in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. t(·) denotes *t*-statistics.

Panel A: Estimates of factor risk premiums

MKT	SMB	HML	Liquidity	PM	Adjusted R^2
0.5387*** (2.98)	0.0127 (0.06)	0.5316*** (3.31)	5.8953*** (2.62)	1.4761* (1.79)	0.6990

Table 10 Continued

Panel B: Pricing error of cross-sectional model										
	Book-to-market equity ratio Quintiles									
Size	low	2	3	4	high	low	2	3	4	high
	$E[R_i - R_f] = \beta_i\lambda + w_i$									
	w					t(w)				
Small	-0.3263	-0.0127	-0.0178	0.0833	0.0735	-3.44	-0.19	-0.30	1.50	0.87
2	0.0099	0.0305	0.0906	0.0309	0.0296	0.16	0.45	1.28	0.43	0.34
3	0.0644	0.0705	-0.0179	0.0061	0.1292	0.94	1.05	-0.25	0.08	1.47
4	0.1024	-0.1124	-0.0311	-0.0026	-0.0897	1.37	-1.61	-0.44	-0.03	-0.95
Big	0.2339	-0.0812	-0.1779	-0.0065	-0.0334	2.66	-1.17	-2.18	-0.08	-0.35